FACULTY OF ECONOMICS AND
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Advanced Geomarketing Modeling Techniques for Retail Networks

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Voorwoord

Na de voltooiing van de opleiding handelsingenieur aan de Universiteit Gent, kreeg ik in 2011 de kans om bij *RetailSonar* aan de slag te gaan (toen nog *Geo Intelligence*). Bij deze toen piepjonge geomarketing onderneming kreeg ik bovendien de mogelijkheid wetenschappelijk onderzoek te verrichten naar klantengedragingsmodellen. Deze klantengedragingsmodellen zouden ook in de praktijk worden toegepast om concrete vragen van retailers te beantwoorden en vormden het speerpunt van het business model van RetailSonar. Ik heb niet lang getwijfeld en de kans met beide handen gegrepen. Het doctoraal project werd een realiteit door de ondersteuning van de Universiteit Gent en van het IWT (onder de vorm van een Baekeland-beurs). Nu, 6 jaar later, wordt er met deze dissertatie een orgelpunt geplaatst op dit traject. De combinatie universiteit-praktijk is een hele uitdaging gebleken. Aan de andere kant heeft de veelheid aan contacten en bijhorende projecten voor een enorme persoonlijke verrijking gezorgd en heeft het tot een verbetering van kennis rond consumentengedragingen en concrete oplossingen voor retailstakeholders geleid. Daarbij heb ik vastgesteld dat zowel de wetenschappelijke als de praktijkmatige zijde veel van elkaar kunnen leren, maar dat dit in het algemeen op erg beperkte schaal gebeurt. De voordelen zijn nochtans duidelijk: retailers en andere stakeholders in het retailproces worden uit eerste hand met nieuwe maatschappelijke uitdagingen en fenomenen geconfronteerd. Ook beschikken zij doorgaans over heel wat unieke data en informatie die inzichten kunnen verschaffen in deze fenomenen. Dit kunnen motoren betekenen voor academisch onderzoek naar een beter begrip van de mens en zijn gedragingen. Aan de andere kant stelt de academische wereld een enorm uitgebreid platform aan inzichten en kennis ter beschikking. Dit contrasteert met de retail-wereld waar kennis nauwelijks wordt gedeeld. Kennis is ten slotte ook een economisch voordeel. Nochtans stelt het delen van kennis zowel onderzoekers als retailers in staat veel gerichter en efficiënter nieuwe en acuratere kennis te ontwikkelen (en steeds vernieuwende competitieve voordelen). Het gebrek aan uitwisseling van gegevens, kennis en oplossingen tussen de academische wereld en de praktijk wordt in de literatuur aangekaart door onder andere Birkin et al. [16]. Het was ook het uitgangspunt van het IWT toen het de Baekeland-mandaten in het leven riep. Met de geleverde publicaties en deze dissertatie hoop ik dan ook een bijgedrage te hebben geleverd aan het slaan van bruggen tussen de wetenschap en de praktijk. Tot slot had ik graag de volgende personen en instanties bedankt voor hun betrokkenheid en hulp:

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Matthias De Beule
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Nederlandstalige Samenvatting

Door de groei van zowel het fysieke winkelaanbod als van de populariteit van het online winkelen, is er sinds enkele tientallen jaren een toegenomen commerciële druk ontstaan op de fysieke retailorganisaties. Retailers zijn genoodzaakt om op een meer actieve manier te concurreren voor hun klanten terwijl investeringsbeslissingen op steeds kortere termijnen moeten worden genomen. Hun kennis over consumenten en klanten is tegelijkertijd ook toegenomen. Spatial Decision Support Systems zijn bij retailers daarom populairder geworden omdat ze grotere en steeds accuratere datasets over zowel klanten als niet-klanten, concurrenten en maatschappij kunnen vertalen naar inzichten. Op die manier bieden ze ondersteuning in het nemen van snellere en betere beslissingen. Expansie managers kunnen bijvoorbeeld van verschillende gegevenssets gebruik maken om beslissingen rond locaties van winkelopeningen, -aanpassingen of -sluitingen te onderbouwen. Een vaak gebruikte geomarketing techniek om de financiële weerslag van deze beslissingen te becijferen is Spatial Interaction Modeling (SIM). SIM modelleert ruimtelijk consumentengedrag onder de vorm van koopstromen. Deze gemodelleerde interacties *stromen* van geografisch geaggregeerde consumentengebieden naar de verschillende winkels waar er aankopen van de bestudeerde markt plaatsvinden. Deze winkels concurreren voor het bestedingspotentieel van consumenten door een op zwaartekracht gelijkende aantrekkingskracht uit te oefenen op de lokale consument, waarvan de grootte afhangt van zowel winkel- als consumentenkenmerken en de ruimtelijke afstand tussen beiden. De parameters van een SIM, die deze dynamieken wegen, worden geoptimaliseerd door het model te vergelijken met waargenomen koopstromen (afgeleid uit bijvoorbeeld klantenkaarten) en winkel- en ketenomzetten. Dit doctoraatsverslag heeft als eerste doel om het fundamenteel begrip te verbeteren van twee specifieke elementen van ruimtelijk consumentengedrag: Hoe consumenten hun budget verdelen in twee of meer winkels van dezelfde keten wanneer deze naburige winkels actief om dezelfde consument concurreren, wat ook gekend staat als omzetkannibalisatie, en wat de impact is van het type en bepaalde kenmerken van het omvattende winkelgebied op de keuze van winkel of winkelgebied. Dit doctoraatsverslag heeft als tweede doel om aan te tonen dat een SIM zeer goed toepasbaar kan zijn voor het beantwoorden van locatievraagstukken in de praktijk.

Hoofdstuk 2 bouwt van een predictief spatial interaction model voor de Belgische voedingsmarkt dat zich baseert op basis datasets en dat erg robuuste voorspellingen oplevert door de resultaten te valideren met werkelijke performantiedata op verschillende niveaus. Het in de literatuur bestaande model wordt bovendien uitgebreid met klantendynamieken rond omzetkannibalisatie en er wordt aangetoond dat dit leidt tot een hogere voorspellingsaccuraatheid. Hoofdstuk 3 kijkt op een meer algemene manier naar omzetkannibalisatiedynamieken en maakt een vergelijkende studie van verzorgingsgebieden van verschillende types retailers waarin omzetkannibalisatie wordt verwacht. Verschillende mates van omzetkannibalisatie worden vastgesteld naargelang het type product en de locatiestrategie van de bestudeerde retailers. Ook wordt er vastgesteld dat het winkelgebied waar de winkel is gelegen een invloed uitoefent op de ruimtelijke concurrentie binnen een keten. Hoofdstuk 4 graaft dieper in het concept van winkelgebieden en legt de link tussen het commerciële succes van het aanbod van periodieke goederen (zoals kleding of schoenen) binnen twee types winkelgebieden in Vlaanderen (stadscentra en baanconcentraties) en verschillende kenmerken van deze gebieden. Deze kenmerken zijn gebaseerd op de kwalitatieve input van een consumentenbevraging over winkelgebieden en kwantitatieve metrieken over hun ruimtelijke samenstelling. Commercieel succes van shoppingretail binnen stadscentra hangt voornamelijk af van omgevings- en sociale aspecten, terwijl commercieel succes in baanconcentraties voornamelijk afhangt van de bereikbaarheid met de wagen.

Tot slot wordt er aangetoond dat de resultaten van deze dissertatie nuttig kunnen zijn voor verschillende retailstakeholders: voor retailers zelf, maar tevens voor vastgoedontwikkelaars en -managers, en voor beleidsmakers en ruimtelijke planners.

Summary

In the last decades, physical retail has come under severe pressure, due to growth of both physical and e-retailing supply. While retailers have to rival more intensely for consumers with shortening decision-windows, their understanding on the very same consumer has also grown. This improved understanding is facilitated by the rise of Spatial Decision Support Systems that combine sets of high-quality data on both customers and non-customers and computation power to turn these data into actionable insights. Location planners can now use transactional, socio-demographic and store-related data to make better decisions on store openings, modifications or closings. A popular geomarketing technique to predict the financial outcome of such decisions is Spatial Interaction Modeling (SIM). SIM models spatial consumer behaviour as monetary expenditure flows from geo-referenced, aggregated consumer origins towards stores. These stores compete for the consumer spending potential by exerting a gravity-force like attraction on consumers, with the magnitude of attraction depending on store and consumer attributes and the geographical distance between both. The parameters of a SIM are optimized based on observed but partial expenditure flows (based on f.e. loyalty cards), store and enterprise turnovers. This dissertation aims firstly at improving the fundamental understanding of two specific spatial consumer behaviour aspects: the specific choice dynamics of consumers for which two or more stores of the same brand spatially compete (sales cannibalization) and the impact of the features and format of the superordinate retail area on store (area) choice. Secondly, this dissertation aims at ensuring that a SIM is highly applicable for location planners in practice.

Chapter 2 constructs a predictive spatial interaction model for the Belgian grocery market that is based on basic data sets and that yields robust predictions thanks to result validation on several levels of observed performance data. The incumbent model formulation is extended to incorporate sales cannibalization dynamics and it is proven that it contributes to the overall predictive power of the model. Chapter 3 looks to the sales cannibalization dynamics beyond the grocery market and makes a multi-retailer comparative study of store trade areas where sales cannibalization is likely to be present. Varying degrees of sales cannibalization are detected across product types and expansion strategies. Moreover, a varying impact of the superordinate retail area on sales cannibalization is found. Chapter 4 elaborates further on retail areas and links the commercial success for shopping-oriented goods within two shopping area formats in Flanders (city centers and out-of-town shopping strips) to different attributes. These attributes are based on qualitative input from a consumer survey and quantitative spatial configuration metrics. City center commercial success mainly depends on ambient and social elements, while commercial success for the same goods for shopping strips depends on its accessibility by car.

Finally, it is shown that the findings of this dissertation are useful for different retail stakeholders: retailers, retail real estate developers and managers, and government urban planners and policy makers.

1
Introduction

1.1 Context and Motivation

Retailing *includes all the activities in selling products or services directly to final consumers for their personal, non-business use* [78]. Retailers are well-know to consumers as they act as contact points in the final stages of the production-to-consumption process. Different forms of retail contact points exist, like classic brick-and-mortar stores (Wal-Mart, Colruyt), direct sales channels (sales call-centers) or, with increasing popularity, e-retail platforms (websites or apps) (Amazon, Cool-Blue). Retailing represents a major part of the the entire economy, covering 11% of total employment and 10% of total turnover in Europe in 2013 [135].

In recent years, the retail sector in Europe has seen increasingly fierce competition. The total sales surface by brick-and-mortar stores throughout Europe grew annually by more than 1.2% [52, 53]. Meanwhile, sales through e-commerce rose to between 6% and 8% of total retail turnover in 2016 [26, 44] with total volume in retail trade growing only marginally or even stabilizing in Western Europe [43]. This increased competition is re-shaping the retail landscape with waves of cost-saving consolidations, on average increasing store sizes and, ultimately, retail bankruptcies [42].

As a result, retailers have to increase efforts to actively rival for, attract and ultimately persuade consumers to spend on their products or services. Retailers compete with one another for customers in offering the right goods or services [1], at the right location [31], for the right price [14] and with the right message [119]. These instruments of the retail marketing mix are also known as the $4P's$ in a transactional context (like grocery shopping): Product, Place, Price & Promotion [92]. More recently, a variant consisting of $4C's$

(Clients, Convenience, Costs & Communications) was introduced for retailing that involves long-term consumer relationships (like financial services) [87].

To improve its competitive edge, a retailer has to invest in all of these leverages, while being faced with a limited investment budget and shortening evaluation cycles. It is thus of the utmost importance that the right investments are done at the right time. This has become an increasingly challenging task in the fast evolving retail markets. But, while the competition for the consumer has increased, so has the understanding of them. Decision-Support Systems (DSS) can now aid retailers in improving the understanding of consumers and can allow them to make better investment decisions. This type of system comprises a set of related computer programs, algorithms and data that assist decision-makers with analysis and the decision making itself. More and higher quality data on consumers can now be obtained from third parties in the information industry or can be captured by the retailers during customer communication or transactions. Increased computation power has, in turn, enabled retailers to analyze these data (themselves) and to use complex mathematical models and algorithms to better understand and predict consumer behaviour. This improved understanding and predictive capability enables a retailer to derive actions and strategies on customer, store, enterprise and market level in order to increase its competitive edge and to re-invigorate profitability [63, 81] (see Table 1.1).

This dissertation focuses specifically on store-level instruments and leverages of the retail marketing mix. These instruments and leverages are usually handled by the profession of *location planning*. Location planners are often charged with the operationalization of the store network related part of the strategic plan drawn by top company-executives. It is characterized by making long term decisions and commitments like opening, modifying or closing stores, hence they are often seen as strategic decisions in nature as well. By contrast, decisions on other instruments of the marketing mix are usually of shorter term, for which retailers are often seen as more responsive to [63]. Such an inertia in decision making on the store network can often forgo opportunities that in hindsight would have been ideal in support of the strategic plan. This again shows the importance of decision-support tools for location planners that speed up decision making with higher degrees of confidence. To this end, Spatial Decision-Support Systems (SDSS) have become widely accessible for retail location planners in the last two decades, thanks to the increased availability of vast sets of geo-referenced consumer data and the increased computation power to turn these data into spatial insights. Examples of the former are data on customers generated through loyalty cards or road network data under the Open Data standard like OpenStreetMap [1]. A more elaborate overview on various geo-referenced datasets is provided in section 1.3.

Moreover, the profession of location planning is not restricted to location decisions alone but links to tactical or operational decision making on other instruments of the marketing mix, like store-level price setting of promotion campaigning.

To aid location planners in making better and faster decisions on all leverages of the

[1] https://www.openstreetmap.org/

LEVEL	CATEGORY	EXAMPLE KEY ATTRIBUTES	EXAMPLE DECISIONS
Market	Competition	Competitive concentration in terms of market-share	Market entry/expansion
	Market structure	Product heterogeneity and disruption. Sales channels used in market	Business model creation
	Price	Cost-of-goods-sold and perceived value	Overal price-level
	Power	Negotiation power towards manufacturers or wholesalers	Cooperation or competition
	Advertising	Consumer response to advertising aimed at brand recognition	Above the line advertising campaigns
Enterprise	Cooperation	Synergies through non-organic growth or alliances	Mergers & acquisitions, purchasing alliance
	Branding	Marketing of Unique Selling Proposition (USP)	Price and quality consciousness campaigns
	Sales channels	Different channels to make offering available to consumers	Multi-channel sales approach
Store	Place	Geographic market coverage with current network and detection of blindspots	New store location
	Price	Profit maximization given local customers and competition	Local price setting
	Promotion	Set of local marketing actions	Monthly leaflet distribution around store
	Product	Products fitting best the size and desires of local market	Product assortment per store
	Distribution	Organization of inbound logistics	Stock levels in each store
Costumer	Satisfaction	Measurements of previous encounters with company	Personal management of bad experiences
	Loyalty	Creation of lock-ins driven by positive attitude	Loyalty programs & communication
	Profitability	Measurement of effort versus sales per customer	Focus resources on most profitable customers

Table 1.1: Retailer strategies and actions on different levels. Based on Kumar et al. [81]

retail marketing mix, this research aims in first place at improving understanding on how consumers weigh different elements to one another in their store visiting choice. The varying, intertwined elements of spatial consumer behaviour can be categorized as follows:

- **Store proximity** describes the role of the physical separation between consumer and store and is rooted in the benefits seen by consumers in a lower time-cost of traveling (or a higher convenience) in visiting a store that is located nearby. Hence, all other elements being equal, consumers tend to visit a store that is located closer more often than another store located further away, although the degree varies across segments of retail.
- **Store features** encompass all elements innate to the store itself that can be seen by consumers as persuasive elements to visit that store over another. As an example, a bigger, fresher looking store with more parking spots than another store is, all other elements being equal, more preferable to visit over the other. On top of these

elements, the brand of a store can influence store choice due to brand loyalty.

- **Store environment features** relate to the fact that a store does not operate in isolation, but is part of a spatial tissue where various activities (like other retail, work or leisure) take place and intertwine. Retailers often actively seek these proximity interdepencies in their location choice [80] because co-location can yield various positive externalities [19]. One externality that is of particular interest to this dissertation, is an increased visit preference for a store that is central to other activities over an isolated store. In the consumer's desire to minimize travel costs, visiting a store that is located close to other activities might reduce overall travel time when visits to these other activities are combined in one multipurpose trip [4]. Moreover, a store's environment exhales certain atmospherics, a qualitative perception by consumer on the pleasantness of spending time in this environment, which might influence store choice as well. A deeper understanding of the role of the environment on the store's performance, can learn location planners to expand the store network to the right habitats.

- **Consumer socio-demographic attributes** refer to all personal characteristics of a consumer, like age and social class. Local consumer attributes influence a store's success in two ways. First of all, the attributes determine a consumer's total budget they are willing or able to spend on the kind of products and services offered by a store. As an example, higher social classes are spending on average more on clothing than lower social classes. Secondly, they influence the consumer's propensity of spending a part of that budget in a store offering versions of products or services that are (not) in line with the consumer's desires. For example, higher social classes are more attracted to stores offering upmarket versions of certain goods or services. By knowing the ideal customer profile, location planners can, for example, detect certain areas with the most fitting profile for future expansion.

Secondly, this dissertation aims at showcasing how the aforementioned elements are integrated in a geomarketing model. These models, when integrated in an SDSS, can be used to simulate consumer behaviour in relation to store choice and can forecast the success of location-based decisions (a) by different metrics, (b) with higher speed and (c) with higher accuracy. An example of such simulation is estimating the annual turnover of a new store, while simultaneously estimating the impact on the performance of neighbouring stores as well as estimating the client attraction area (the trade area) of the new store for marketing purposes (for a store launch campaign in certain towns). Moreover, an SDSS allows location planners to test different decision scenarios in which varying configuration of store choice elements are imputed. Knowing the expected return of each scenario before the actual decision is made, can then lead to better decision making.

The next sections discuss geomarketing models in larger detail. Section 1.2 starts with an outline of different geomarketing models that are used in location planning. The type of model that is most frequently used throughout this dissertation (Spatial Interaction Modeling (SIM)) is then discussed in more detail. Subsequently, section 1.3 identifies types and sources of data most commonly used in geomarketing models. Finally, section 1.4 gives a high-level overview on the contributions made in this dissertation on a better understanding of spatial consumer behaviour in retail and on extending geomarketing models with these learnings. It also refers to following chapters in which academic papers are presented where the contributions are presented in full detail.

1.2 Geomarketing Modeling Techniques

1.2.1 Overview

Geomarketing models support location planners in translating data into insights on spatial consumer behaviour and facilitate them with predictions on the impact of store network changes. Throughout the history of retailing, various techniques have grown organically or have been developed to this end. These techniques range from very basic, intuitive, cheap-to-implement techniques to very sophisticated mathematical modeling and solving techniques with higher setup and maintenance costs. Generally speaking, three major categories can be distinguished, ranked on their degree of complexity: knowledge based techniques, comparative techniques and predictive techniques [11, 63, 140].

Knowledge based techniques

The most common technique that is based on knowledge, consists of relying on the experience and gut feeling by senior expansion managers to estimate the value of an expansion location and the impact on neighbouring stores. While very little data or costs are involved with this technique, gauging the quality of a location is arguably very subjective in nature, prone to human interpretation mistakes. With the rise of Geographic Information Systems (GIS), a more data-rich variant on gut feel estimations emerged. Different zones around a location under study are arbitrarily defined and information on competitor stores or social classes from different GIS layers are mapped in each zone. With this information, a gut-feeling estimation is made on the expected consumer attraction per zone (also known as 'using ratios'). Based on these partial estimations, an overall estimation and evaluation of the location is made.

Comparative techniques

A more advanced, data-intensive set of techniques is known as comparative techniques. The most basic comparative technique stems from following behaviour [27]. A retailer evaluates a location as positive if a leading retailer (*anchor store*) is already present nearby. This technique is mainly observed for high street retailers that bank on impulse buying behaviour of shoppers that originally were attracted to the anchor store nearby.

A retailer can also compare a location under study to an existing store in its own network that closely matches in local socio-demographics, competition and store (environment) features. While this technique can take a multitude of different comparative aspects into account, its reliability largely depends on the diversity of stores in the current network and whether all elements can be seen are transferable to the location under study (for example: what if the most comparable store overperfoms?). Another comparative technique consists of listing features of well performing stores from experience or data. Next, a score-card or a checklist is constructed after which a location under study must achieve a minimum score or minimum number of checks before being evaluated as positive.

Predictive modeling techniques

A final category of techniques encompass the use of predictive models for store performance. A well-known technique for understanding store performance and using it in a predictive way consists of a multivariate regression technique. Various indicators on local socio-demographics, competition, environment and features on the store themselves are inventoried and used as independent variables. A store's annual turnover is usually taken as dependent variable. After statistical optimization, the resulting set of parameters and confidence show the relevance and importance of each feature to store performance. They can also be transferred to the indicators of a location under study to estimate its turnover potential. A major drawback of this technique is that it neglects the specific spatial configuration of the retailing process, especially in relation to the competitor stores [15]. In chapter 4, the multivariate regression technique is applied to predict the success of shopping areas. To overcome its aforementioned shortcoming, the spatial configuration of the local retailing process is taken into account as an independent variable in the regression.

A more advanced technique where the spatial configuration is part of its core structure is called Spatial Interaction Modeling (SIM). This technique models expenditure or buying flows between the geographically distributed consumers (origins) and stores (destinations). In simple words, it predicts how much is spent by consumers from one geographical area in each store. The magnitude of such flow depends on (a) features of the consumers themselves, (b) the attraction of the stores exerted on the consumers (driven by store features or features of its environment) and (c) the distance between consumer and store (also known as the *interaction* between both). By adding a new destination that generates attraction to the model (the location under study), the estimated expenditure flows will adapt and a store turnover is predicted. As spatial interaction modeling is used and extended in this dissertation, a more elaborate explanation on SIM is given in section 1.2.2.

Finally, recent techniques as Machine Learning (ML) open new perspectives to predictive store modeling. ML predictive techniques are characterized by the absence of an a priori model structure and let algorithms form the model structure and parametrization based on pattern recognition in the data. Due to its complex nature, transparency and robustness (risk of overfitting the data) are major points of attention when applying these techniques. While these techniques have become popular in other areas of retail like advertising [120], pricing [45] and stock replenishment [71, 141], much less applications of ML have been found in retail location planning. Stahlbock et al. [124] provide an early attempt, using an ML technique (*Artificial Neural Nets*) to estimate rough store turnovers. Krause-Traudes et al. [79] used a *Support Vector Regression*-type of model which gave satisfactory predictive results after iteratively incorporating more independent variables, although no external validity of the model is presented. A paper by Fischer [47] is limited to a methodological outline of a spatial ML model. Nonetheless, these techniques show great promise as optimization methods [12] and even as model formulators of geomarketing models. While this set of techniques is not used in this dissertation, a suggestion for future research using ML techniques for location planning is proposed in section 5.3.3.

1.2.2 Spatial Interaction Modelling (SIM)

In the broad class of social simulations, a Spatial Interaction Model (SIM) is a model that mimics any movement over space that results from a human process [61]. In a retail context, SIM's simulate magnitudes of expenditure flows between consumers and stores. Consumers, the origins of the flows, are characterized by various socio-demographic features and are modeled on an aggregated, but small-area level (for example, polygons like statistical blocks or postal codes). In the remainder of this dissertation, the terms *origins, blocks* or *zones* all refer to these polygons. In turn, stores are seen as destinations of the flows and also possess various features, as discussed earlier. The interaction between both is based on Newton's scientific theory of Universal Gravitation (hence the well known synonym *gravity model*). As shown in Figure 1.1, stores are seen as attraction poles that pull on consumers *(1)* which are constrained by distance *(2)*. This attraction (which is based on distance, consumer and store features) generates the expenditure flows *(3)* and subsequently store revenues that are registered by the retailer *(4)*.

Subsequently, the optimization of a SIM consists of estimating the modeled expenditure flows to a best degree of fit to partial information on observed expenditure flows within systemic constraints. The observed expenditure flows can, for example, be based on purchase transactions linked to loyalty cards or alternatively on aggregates like turnover figures on store and even enterprise level. An example of the systemic constraints consists of constraining the total magnitude of expenditure flows originating from each zone to the geographic demand potential of that zone. The original model definition was proposed by Huff more than 50 years ago [65]. Ever since, a SIM is also known as a *Huff model*. In the remainder of this dissertation SIM, Huff or gravity model are used interchangeably to denominate this type of model.

Model formulation

A SIM ultimately predicts all expenditure flows between consumer origins and stores. An expenditure flow from an origin to a store is seen as a fraction of the total expenditure potential for goods or services offered in the retail market segment under study by all con-

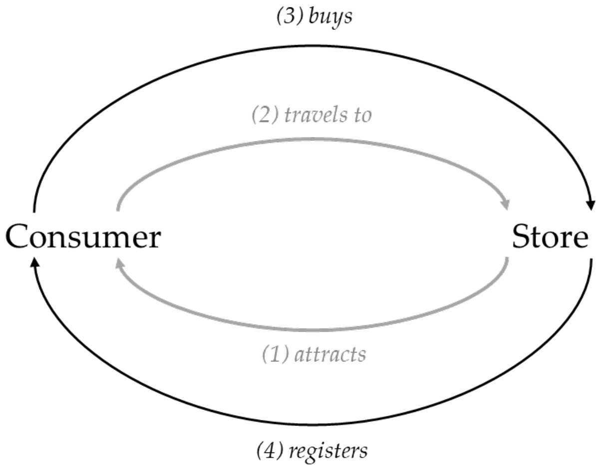

Figure 1.1: Graphical depiction of the retailing process in a SIM.

sumers in that origin. This fraction can thus also be seen as a patronage probability (a visit probability or visit propensity) by consumers in origin i towards store j:

$$F_{ij} = P_{ij} \cdot SP_i \tag{1.1}$$

where F_{ij} equals the expenditure flow between store j and origin i, P_{ij} is the patronage probability of a store j for consumers in a given origin i and SP_i is the total spending potential of all consumers of origin i. The estimation of SP_i is an important building block for any SIM and is discussed thoroughly later on. In a spatial interaction model, the patronage probability P_{ij} equals the proportional utility of this store (U_{ij}) compared to the total utility generated by all N stores (including competitors') in the neighbourhood of this origin:

$$P_{ij} = \frac{U_{ij}}{\sum_{q=1}^{N} U_{iq}} \tag{1.2}$$

where N is the set of stores that exert reasonable attraction on consumers of origin i.

The utility generated by store j for residents of origin i is calculated as:

$$U_{ij} = \frac{A_j}{{D_{ij}}^{\beta}} \tag{1.3}$$

The value A_j represents the attractiveness component reflecting features of store j and its environment. In the basic Huff model, only store size is used for A_j. However, this store attraction component has been extended with other features ever since, which is discussed in detail later on. Finally, D_{ij} is the distance (or any distance related metric) between store j and consumers of origin i and is taken into account to model the spatial interaction between consumers and stores. It can be seen from the above formula that with a positive parameter β, an increasing distance has a diminishing effect on store utility. This contrasts in general with the positive influence of store-related features on store utility. Hence the distance component is often seen as the *deterrence* factor.

In the following paragraphs, we discuss the three major building blocks of a SIM in more detail and we present extensions to the basic model found in literature.

1.2.2.1 Demand

As mentioned before, an important first step in the construction of a spatial interaction model is the estimation of the local spending potential SP_i. As a starting point for this discussion, it is assumed that all demand arises from the residential location of a consumer, which is to date most commonly used in spatial interaction models (later on this assumption will be relaxed). SP_i can then be constructed in following general way:

$$SP_i = B \cdot P_i \cdot \theta_i^{\gamma} \tag{1.4}$$

Where B is an estimation on the basic spending potential per capita for products or services offered by the focal retailer. This can often be found in market reports on the retailing segment under study, or proposed by senior employees of the retailing firm based on experience, or it can even be derived from actual customer spending. P_i represents the total relevant population in origin i. Finally, θ_i can represent any normalized socio-demographic feature of origin i that has an influence on the basic spending potential (for example a wealth index). γ is the parameter to which θ_i is raised and models the relationship (or elasticity) between the socio-demographic feature and the actual spending potential. If, for example, θ_i represents the wealth index of origin i and the spending potential for daily grocery shopping is estimated, γ will be smaller than 1. For luxury goods, γ will be larger than 1. Naturally, other, mutually uncorrelated socio-demographic features can be added in an additive or multiplicative way. In case of an additive relation, each term has its own weighting factor. In case of a multiplicative relationship, each term is raised to its respective power argument (with γ provided here as a general term). In section 1.3.2, the scope and sources of data on socio-demographic features and observed expenditure flows are outlined in more detail.

Of course, not all demand arises from the residential location of the consumer. Contemporary consumers shop from their workplace as well, or chain shopping with other activities in one trip [6, 22], making the true origin of the expenditure flow somewhat blurred. One way to cope with this phenomenon is to use demand disaggregation in the calculation of local spending potential. As used in chapter 2 and by Birkin et al. [16], data are gathered on the geographic spread of workplaces per consumer origin area. An average fraction of the total spending potential that either originated from the home or from the work location is then estimated. This yields a per origin estimation of residential and work related spending potential. Newing et al. [98] used the same approach for complementing residential potential with additional spending potential from local touristic stays. Subsequently, separate store utility functions and spatial interaction dynamics for both activities can be estimated. For example, demand originating from working places can be more spatially constrained than residential demand (larger $beta$ coefficient in equation 1.3). Another way to integrate the effect of multiple origins, is discussed in next section.

1.2.2.2 Supply

The notion of supply in a SIM refers to store features (or store environment features) that drive the attractiveness component A_j for store j. The general formulation of this component can be written as follows:

$$A_{j|j \in b} = S_j^{\alpha} \cdot \lambda_j^{\kappa} \cdot R_b \tag{1.5}$$

where $A_{j|j \in b}$ is the store attractiveness component for store j belonging to store network of retailer (or brand) b. A multitude of store-related features can be integrated in this component, with the net sales space of a store as most basic element. S_j refers to the sales area of store j which is raised to the power α. α is usually set between 0 and 1, mimicking the diminishing marginal sales space productivity as total sales space increases. Retail segments that are characterized by significant positive size-effects however (like clothing), can witness $\alpha > 1$. Next, λ_j is a summarizing term reflecting all other possible store or store environment related features. Their mutual relation can be additive (with individual weight terms) or multiplicative. In case of the latter they can be individually raised to a certain power (with κ used as their general term). Examples of other store features that have been included in previous studies, encompass the store concept [58, 101], brand image [125], number of parking spots available [133], and the speed of checkout service [25]. Also, more time-driven features can be integrated like in 'years in operation' or 'years since latest refurbishment'. When these effects of time are estimated, it effectively turns the spatial model into a spatiotemporal model, enabling to predict the specific growth path of a new store over coming years. Store environment features, in turn, can refer to the attractiveness of a store derived from other activities nearby and from the qualitative perception of its environment. Example neighbouring activities are workplaces, schools, hospitals, or even leisure or culture venues. A special case of improved attractiveness is found when other retailers cluster in close proximity of one another in a retail agglomeration (e.g. city center high streets, shopping malls or peripheral shopping strips). The combined consumer attraction of these stores might surpass the sum of their individual attractions, due to time-saving benefits derived from a one-stop multi-shopping visit [4, 5, 7]. In a spatial interaction model, this non-competitive, positive influence of neighbouring activity is integrated in the focal store's utility function. In doing so, it presents a different modeling approach than the demand disaggregation approach that is proposed in section 1.2.2.1, where neighbouring activity is integrated in a SIM as partial, separate sources of demand that interact with the focal store[2]. We refer to the newly presented approach as ‘residential trip-chaining’, in line with research by Arentze et al. [6] on this topic. Crucially, residential trip-chaining models only one interaction with a store per consumer, always originating from the consumer’s residential origin, while demand disaggregation models multiple interactions per consumer, stemming from various origins across all activities in scope. Panel A of Figure 1.2 shows an example on how residential trip chaining can be modeled. Expenditure flows are limited to residential origins with the store attractiveness depending on neighbouring activities. The incorporation of this approach for multiple activities in a SIM is elaborated further as a suggestion for future research in section 5.3.2. Panel B of Figure 1.2 on the other hand, shows the outline of demand disaggregation, where all activities are modeled as independent demand origins.

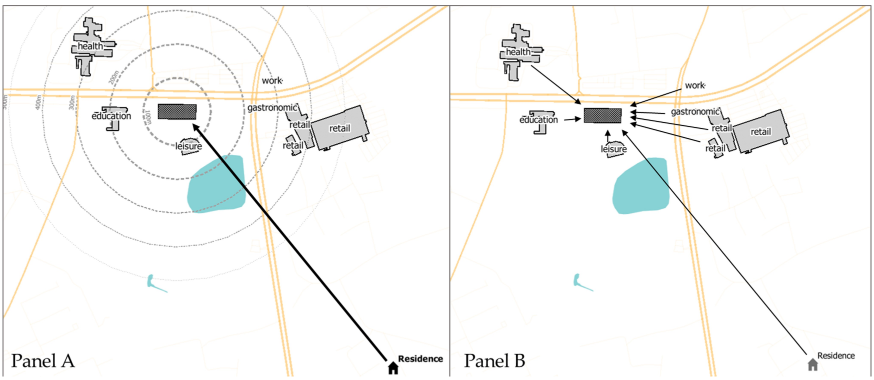

Figure 1.2: Example depiction of modeling residential trip-chaining in panel A and demand disaggregation in panel B.

Both approaches can be applied to model the influence of neighbouring activities, where they exhibit different modeling strengths and weaknesses: First, residential trip-chaining only requires one global demand estimation, while demand disaggregation requires a separate, partial demand potential estimation per activity origin, which is a more time-consuming and difficult task (see section 1.3.4). On the other hand, demand disaggregation entails having different model parameters per activity, which allows a more accurate modeling of the specific interaction between the demand generated from each activity and the stores in the model. In line with this, demand disaggregation is not spatially limited to an a priori defined ‘agglomeration edge’ as is the case for residential trip-chaining (with edges of influence often less than 1 kilometer). This edge is, for example, a suboptimal representation of the spatial sphere of influence of commuting-related demand, as shopping for distinct products is often taking place on daily commuting trips. On the other hand,

[2]Demand disaggregation is presented in section 1.2.2.1 for workplaces and tourism, but can be applied to retail or other activities as well

for demand during work breaks, the spatially constrained residential trip-chaining approach is much more straightforward. Finally, the use of demand disaggregation obstructs fine-grained model validation to a certain degree. When validating a model, observed expenditure flows can be compared to their modeled counterparts (see section 1.2.3). Purchasing information linked to loyalty cards can be used to yield these observed expenditure flows. However, loyalty cards register only the residential address of the customer, hence all observed expenditure flows refer by default to the residential origin of the customer. Demand disaggregation however, yields modeled expenditure flows from multiple demand origins, which makes goodness-of-fit metrics of the model on expenditure flow level less valuable. By contrast, residential trip-chaining does not suffer from this and both modeled and observed expenditure flows can be compared in a straightforward way. The choice of approach -or a combination of both- then ultimately depends to a large degree on the studied market: (a) what non-residential activities are important to trip-chaining with a store in this market; (b) what is the expected spatial constraint of the chains with these activities; (c) what data is available on the location and size of other activities (see sections 1.3.3 and 1.3.4); and (d) what validation information for model optimization is available. In general, residential trip-chaining and agglomeration clusters are used for retail because of the inherent spatial constraint of mutual influence. On the other hand, demand disaggregation is usually applied for workplaces because of an easier partial demand estimation and less spatial constraint.

Finally, R_b refers to the basic attraction value for all stores of retailer b. This competitor-specific factor reflects other store-choice influencing elements on enterprise, store or consumer level. Examples like shelve density, price setting, customer loyalty (programs) or customer engagement through personal communication all have their effect on brand and thus individual store choice. On the other hand, decisions on these leverages of consumer attraction are often outside the area of direct responsibility of location planners, hence, in a SIM, they are seen as a given and their global impact on consumer attraction is taken into account. A factor derived from the average sales space productivity per competitor can be used as a proxy, as more successful retailers in terms of price setting, customer loyalty and engagement tend to have higher average sales space productivity than their competitors. Alternatively, these competitor-specific factors can be estimated as well. The different data sources for store-related features are discussed in more detail in section 1.3.3.

1.2.2.3 Interaction between demand and supply

When a consumer travels to a store, the consumer invests in a time-cost to overcome his physical separation with that store. A consumer weighs its perceived travel-cost to all stores in its store choice set, including competitor stores as well as alternative stores of the same retailer. Stores that require a too large travel cost are quickly discarded from a consumer's store choice set, resulting in N stores in the consumer's store choice set (see Equation 1.2). The $\frac{1}{D_{ij}^{\beta}}$ term refers to the interaction between demand origin i and stores j in the choice set of this origin. D_{ij} is calculated as the distance (or travel time) between the consumer (usually the centroid of the small-scale area of its residence) and the store. Methods of calculating distances or time-costs are discussed further in section 1.3.5. Because travel time is seen as a cost, the factor β, that controls the weight of travel cost on utility, is positive and larger than 1. The latter means a bigger travel cost results in a more than proportional reduction in willingness or propensity to travel towards that store.

β can also be differentiated according to store related features. For example, a larger store concept like a hypermarket, is likely to have different spatial interaction effects on consumers than a local grocery store, as will be shown in chapter 2. Demand related features can also influence the β-coefficient. For example, Wilson [139] incorporated a transportation modal preference to and from a store that depended on the socio-demographic attributes of a consumer zone. Next to physical separation between demand and supply, a preference separation can exist between consumers and the versions of products each store (or brand) offers. This disaggregated brand preference turns the store attraction component A_j of equation 1.3 into a consumer origin depending factor A_{ij} based on the preference hierarchy of certain socio-demographic groups towards each brand [139]. However, the incorporation of this disaggregated brand preference in a SIM largely depends on the availability of the right socio-demographic data to make these clusters and preference structures, as will be shown in section 1.3.2.

1.2.3 SIM optimization and validation

By incorporating all individual drivers for store success with a weighting parameter, the spatial interaction model can be optimized in a mathematical way. The optimization aims at rendering expenditure flows F_{ij} between all origins i and all stores j in the model (including competitors), such that (aggregations of) these expenditure flows match their observed counterparts as closely as possibly. The different levels of observed performance data that are used for model optimization and validation are discussed in section 1.3.

Optimization methods

When the SIM is modeled in a multiplicative way as presented in section 1.2.2, Nakanishi and Cooper [97] showed a strategy to estimate model parameters using ordinary least square estimations when a log transformation is applied to the SIM-components. However, a non-multiplicative variant is used in this dissertation to model spatial consumer behaviour more accurately. As no optimization method exists that yields the optimal parameter set of such model within a reasonable time window, it induces the use of metaheuristics to approximate optimal model parametrization (see section 1.4). Also, machine learning techniques as proposed in section 1.2.1 can be used to this end.

Validation: Goodness-Of-Fit

Several metrics that capture the fit between the modeled and observed expenditure flows (or their aggregates to store or enterprise level) can be calculated:

- A variation on the coefficient of determination (R^2) is often used in literature as Goodness-of-Fit-indicator for SIM's [51]. The pseudo R^2 indicates the level of variance in observed market share that is captured in the modeled market shares. This can be applied to market shares on several levels: from the most fine-grained customer origin level (the expenditure flows), to store or enterprise level. The following mathematical formulation is duplicated from chapter 2:

$$Pseudo\, R^2 = \frac{var(O(MS_n)) - var(\epsilon_n)}{var(O(MS_n))} \tag{1.6}$$

  Where $O(MS_n)$ is the observed market share for area n (origin, store or enterprise level) and $\epsilon_n = O(MS_n) - E(MS_n)$ where $E(MS_n)$ is the expected market share in area n according to the model. During model optimization the pseudo R^2 is maximized, such that the model captures the maximum amount of observed variance.

- The Mean Absolute Percentage Error (MAPE) or Square Root of Mean Squared Percentage Errors (SRMSPE) calculate the percentage error between (aggregated) observed and modeled expenditure flows. By taking the mean absolute value of these deviations, an indication is given to what extent (percentage) the predictions are wrong on average. By squaring the deviations, the SRMSPE is more sensitive to outliers in deviations. The mathematical formulation of MAPE is duplicated from chapter 2:

$$MAPE = \frac{1}{N}\sum_{n=1}^{N} \frac{|O_n - M_n|}{O_n} \tag{1.7}$$

  Where N is the number of observations depending on the level of validation data (costumer origin, store or brand level). O_n is the true observed result for area n, while M_n is the modeled result for area n (if on expenditure flow level, $M_n = F_{ij}$, see equation 1.1). During model optimization the MAPE or SRMSPE is minimized, in order to achieve, on average, the smallest possible mistake.

Validation: Goodness-Of-Forecast

In theory, a location planner can tailor its SIM in such a way that extremely high goodness-of-fit indicators are obtained. In that case however, there is a significant risk that the retail planner has overfitted his model and that it is not as accurate or robust to predictions on future store openings. Therefore it is seen as good practice to test predictions on new stores to actual observed performance after opening. In practice however, it is very difficult to achieve a good base of comparison between both [16]. New stores have to grow to maturity over multiple years before a reliable turnover can be obtained. All the while, the store did not operate in an isolated context: changes in its market or environment could have triggered a different degree of store success than assumed during its performance prediction.

Therefore, a different approach to test model robustness is advocated where predictions are contemporary to the observed performance. For a subset of stores, the training set, all observed information on performance (loyalty cards, store turnover) is used to optimize the model parameters, hence the goodness-of-fit indicators are restricted to this set of stores as well. By contrast, the observed performance information of stores in the validation set is only disclosed and compared to modeled flows *after* model optimization, allowing for an assessment on external model performance. This approach is also used in chapter 2.

Validation: final remarks

As final remarks on model validation, it is also encouraged to plot observed and modeled expenditure flows for each store next to one another in order to gauge model quality from a more qualitative point of view [16]. As not all drivers for store success can reasonably be taken into account in a SIM, it can be of great benefit to discuss the deviations between model and observation with senior location planners that have a more complete, albeit more qualitative, view on local store performance drivers. This process can lead to a shortlist of possible model extensions that subsequently can be tested for their explanatory power from a statistical point of view.

Finally, model deviations on expenditure flow level are usually larger than on store level. A predicted store turnover aggregates individual expenditure flows, thereby naturally reducing error variance. While it is absolutely vital during model optimization to reduce error variance on the finest level in order to capture complex consumer behaviour as accurately as possible, the ultimate investment decision is made on the aggregated store performance. Therefore the store level performance of a model is often presented as the bottom-line indicator of model performance.

1.2.4 SIM benefits

SIM's and other geomarketing models all have the capability of explaining and predicting store performance. However, the explicit modeling of the spatial interaction between consumer and store in the shape of expenditure flows exhibits several additional benefits over other geomarketing models.

First, a SIM is capable of modeling all expenditure flows towards existing and future stores. These flows can be used to complement observed expenditure flows where such observed data is not (yet) available. As an example, for a new store, no geo-referenced purchasing information linked to loyalty card information is yet available. Even a retailer that is entirely without such observed information can get a grasp of its area of customer attraction (the trade area, see Figure 1.4 for an example) for its stores through the use of a SIM. This is, for example, useful for local marketing actions or to get insights on underserved geographical areas.

Secondly, a SIM is also capable of predicting the consumer flows to competitor stores, hence it makes predictions on store performance of competitors as well. This helps location planners to find out where competitors have more attractive locations (to avoid direct competition) or where they can expand more aggressively because of weaker competitor locations.

1.3 Data-sources for SIM

The very first step in a better understanding of actual consumer behaviour in physical retail is to gather various data on the spatial retailing process. This data is inputted in a spatial interaction model and provides input on the actual state of certain consumer, store or interaction elements in the retailing process. A wide variety of data has lately become available [20, 59, 143] and can be categorized as follows:

1.3.1 Transactional data

Consumers can be split into two major groups: existing customers and non-customers. Data on existing customers is usually of high quality and richness as it can be captured thoroughly by the retailer during the retailing process. Loyalty card information, customer registration or shipping information and, to a lesser degree, exit questionnaires (i.e. asking for the customer's postal code at the checkout) can provide such a database of historic transactions between enterprise and customer. These data answer very basic but important questions like *'Who is my customer?'*, *'Where does (s)he come from?'* and *'What does my customer do in contact with me?'* In answering these questions, they exhibit several benefits:

- They allow the identification of the geographic origin of the customer. In most cases this is the home address or home-area like postal code. They are then geo-allocated to a small-scale area (a consumer origin) in a SIM.
- Sales volumes and frequencies can be identified per customer towards each of the stores of the retailer. On store level, sales volume is usually known based on accounting or management reporting figures. After a correction for the partial turnover that could not be linked to geographically referenced origins, observed expenditure flows can be constructed between customer origins and the stores in the retailer's network. Such observed flows are used in model validation.
- Loyalty cards have the additional benefit that often socio-demographic features of the customer are attached to the card. This data is usually provided by the customer when he decided to join the loyalty program.

While methods of capturing transactional data on individual customer level have been around for decades, they are still not widely or actively used by retailers for better location decision making [112].

1.3.2 Socio-demographic data

Socio-demographic data encompass geographically-referenced personal attributes of a client or consumer. Example attributes are age, family size and wealth-class, or more descriptive labels like *'young carrier hunters'* or *'retired hedonists'*. In a spatial interaction model, an annual spending potential is calculated for each small-scale consumer area in scope. The magnitude of such spending potential is closely related to socio-demographic attributes of the consumers in each zone. The relationships between the consumer's features and its spending potential can be derived from current customer spending (while being cautious that even the most successful customer might not spend its entire annual potential in the retailer's stores alone), market reports or the retailer's experience. Also, as discussed in section 1.2.2.3, a disaggregated brand preference based on socio-demographic features can be incorporated. The latter relationships (including towards competitors) usually have to be surveyed by the retailer himself [99].

Loyalty cards provide a variety of attributes on existing customers. A drawback of this source is that it is limited to existing customers only, while information on all consumers in scope is needed for the required analyses and predictions. Alternative sources can provide nation-wide consumer attribute data that are less rich than loyalty card information, but that are sufficient to describe the people living in each area for aggregate predictive modeling purposes. A first such source comes from national statistics agencies that provide spatially referenced, socio-demographic variables for an entire country, with annual updates. An example of these census data in Belgium is provided in Figure 1.3. However, these data are only available as aggregates (averages or totals) within certain delineated zones because of privacy concerns. The smallest granularity of such zones are usually statistical blocks of at least a few hundred inhabitants. Other, more sensitive statistics, are only available on higher levels like municipality-level.

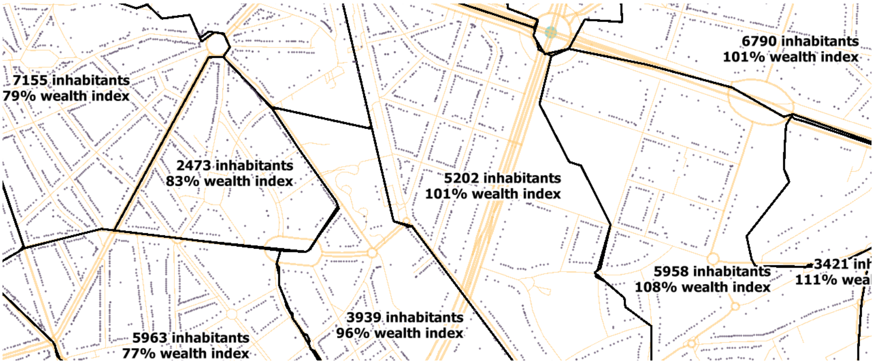

Figure 1.3: Example of census data per statistical zone in Belgium.

Alternatively, more *lifestyle*-related data can be available on the same aggregated levels and are usually supplied by third party providers. Lifestyle-related data use various socio-demographic variables per zone and classify the inhabitants in distinct groups with a descriptive label (for example *wealthy achievers*). Such data then provide the number of consumers per lifestyle-class in each zone.

For potential estimations, census data are preferred over lifestyle data as they provide more variety in per-zone statistics that can be used to construct such potentials. For example, the average wealth and age structure per zone is known in census data, while lifestyle data have a more coarse, descriptive label. Moreover, the exact quantitative range of each variable that make up a lifestyle group is often unknown. On the other hand, the lifestyle-data are preferred for brand preference disaggregation as it is easier to link a descriptive label to the attractiveness towards different retailers. Such labels have indeed innate co-variances (for example, *'retired hedonists'* refer to a subset of consumers of a certain age and wealth class combined). Census data usually do not provide such covariances between different statistics per zone, while third party providers of lifestyle data have come up with per zone covariances based on own research. A trade-off between the use of both sources thus exists, with census data having a slight edge in practice according to Birkin et al. [16]. In this dissertation, we use census data as well, and no research emphasis was put on brand preference disaggregation.

All of the previous sources refer to consumer socio-demographic features from a residential point-of-view. Demand disaggregation however, as described in section 1.2.2.1, splits demand across multiple activity-based origins (like workplaces). Some national statistic agencies provide the number of employees per statistical zone. Alternatively, a partial demand per workplace can be estimated by combining various sources of open or proprietary data from chambers of commerce and accounting reports of enterprises. They allow to detect the location and size of workplaces and the NACE/NAICS-business classification can be used to finetune demand per category of businesses. Data on other types of neighbouring activities are discussed in section 1.3.4.

An important intermediate result of matching observed expenditure flows with geographic spending potential estimates, is the calculation of local market shares and a catchment area of a store. A local market share is calculated as the observed expenditure flow $F_{ij_{obs}}$ divided by the total spending potential SP_i from the same zone and can be seen as the observed visiting probability $P_{ij_{obs}}$ from zone i to store j:

$$P_{ij_{obs}} = \frac{F_{ij_{obs}}}{SP_i} \tag{1.8}$$

The set of zones where the (observed) visiting probability is bigger than zero is a store's catchment area (see Figure 1.4)

1.3.3 Store-related data

Parallel to collecting consumer-related data, data on store locations, their features and environment have to be inventoried. As mentioned before, examples of relevant store features are store sales area, number of parking spots available or 'years since latest refurbishment'. As customers are free to opt to visit competitor stores as well, an inventory on the same features for competitor stores is equally important. For example, in segments of retail that

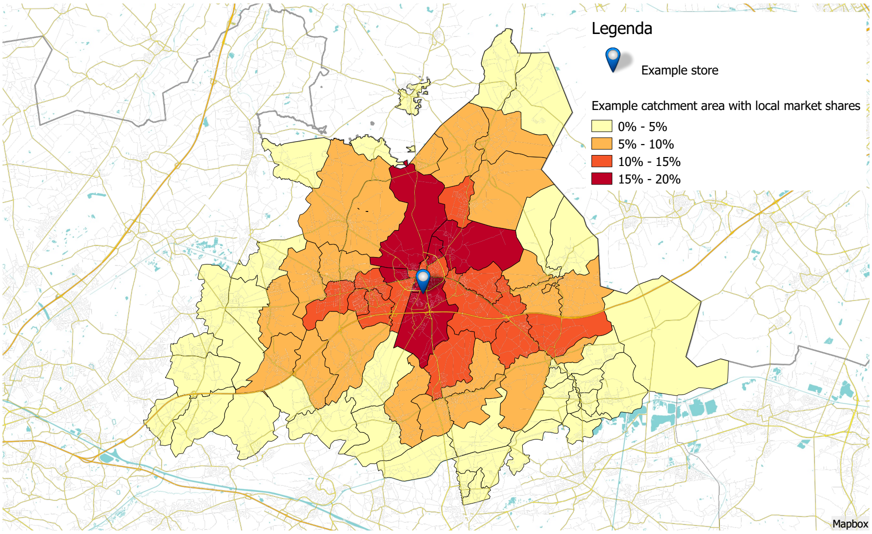

Figure 1.4: Example depiction of zone-based market shares and the catchment area of a store.

offer goods or services through multiple store concepts (f.e. local grocer, supermarket or hypermarket in the grocery market), the concept of each competitor store location should also be inventoried.

While structural, high-quality data on store locations and store features are usually proprietary data that need to be bought from third party suppliers, advances in Open Data on store locations and some of the most important features show promise of equal explanatory power on customer behaviour [90]. Other data on store features have to be inventoried by the retailers themselves (for example 'visibility from the street'), which can be a cumbersome process.

1.3.4 Store-environment data

Data on the store environment can also be taken into account when measuring store attractiveness through residential trip-chaining. A trip to a store can be chained with visits to other activities near the store, in order to reduce the total travel time. To map neighbouring retailers in a retail agglomeration, commercial data is often available. Through advances in Open Data quality, it is now possible to map various other activities surrounding the stores in a structural way (e.g. gastronomic or leisure venues). These sources are however often limited to providing the location of the activity but not its size. For example, OpenStreetMap has a database on *Points-Of-Interest*. Alternatively, data from location-sharing apps (like Swarm) can be used. On a more aggregate level, statistics agencies sometimes provide number of venues per activity type and per statistical zone.

1.3.5 Transportation data

The physical separation between consumers and stores is an important driver for physical store choice. This separation is embedded in the transportation ecosystem in which the consumer travels to the store, buys (an expenditure flow emerges), and returns. Such a local transportation ecosystem encompasses all feasible transportation modals like walking, biking, driving by car or the use of public transportation. The local transportation ecosystem naturally influences the *perceived* proximity by the customer. For example, a poor functioning local road system with high risk on traffic jams effectively lowers the perceived proximity, thereby reducing the store's attractiveness and performance. As a result, any data on the quality of the local transportation ecosystem is very valuable to understand current customer behaviour and to predict future behaviour. Thanks to the increasing quality of proprietary or even Open Data on road networks (including historic traffic jam information) and public transportation, it is now possible to deploy multi-modal routing engines that can calculate travel times for all modes of transportation between customer location and the stores, thereby closely matching the perceived proximity of stores. However, calculating travel times for cars as sole proximity indicator is still the most popular method of calculating store proximity today.

1.3.6 Data on external influences

Data on external influences encompass data on retail-success drivers outside the regular sphere of influence of location planners. This can refer to environmental data or data on other elements of the retail marketing mix that actively influence brand and thus store choice. Regarding environmental data, its inclusion can be valuable to understand historic consumer behaviour and predict consumer behaviour in sectors of retail that are very sensitive to these influences. For example, the measured success of an indoor cinema during a certain time period could be influenced by long periods of bad weather. In turn, the effect of other elements of the marketing mix can be included in a SIM by influencing the store's utility function. However, information on price setting or levels of customer engagement and loyalty for each competitor, are hard to readily apply in this function (but are always useful for additional validation). As mentioned in section 1.2.2.2, a more useful proxy can be constructed by calculating the average sales space productivity (turnover per m^2) per competing retailer. To achieve this, the full turnover from each competitor can be fetched from annual accounting reports and the total sales surface of their physical networks has to be inventoried or bought from a third party information supplier.

1.4 Contributions and Next Chapters

This dissertation aims in the first place to improve the predictive accuracy of a SIM. The predictive accuracy of a SIM stems from a good understanding of spatial consumer behaviour based on analysis of observed behaviour and demand and supply features, and the translation of these insights into a SIM formulation. The emphasis was put on two major research questions:

1. What are the drivers of store choice within a retail network. In other words, how do stores of the same brand spatially compete over the same consumers? The classic SIM formulation models this intra-network competitive dynamic in the same way as spatial competition between stores of different brands. However, literature on sales cannibalization in franchisee networks has already provided empirical evidence this is not correct [70].
2. What is the impact on store choice of features related to the wider retail area where a store is part of? While a large body of literature has been dedicated to understanding the benefits consumers derive from visiting co-located stores, much less research attention has been given to the varying impact of these drivers on actual performance of different formats of retail areas and the influence a retail area has on the local spatial competition for customers within a retailer's store network.

A second goal of this dissertation is to ensure that an improved spatial interaction model remains highly applicable in practice. First, this stems from gathering the right data. As outlined in section 1.3 however, various data are only partially available for a retailer. Some market-wide information can only be purchased at high cost, or can be fetched from Open Data, thereby heavily depending on its completeness. Some attributes are not available through either source and have to be inventoried by the retailer himself. This makes the incorporation of certain store choice features discovered in literature cost-ineffective or even impossible. Secondly, high applicability entails the need of a SIM to be robust in its predictions. Robustness can be increased by comparing observed and modeled results as much as possible and increasing their fit. Fine-grained expenditure flow information can be used to fine-tune spatial interaction dynamics in a robust way, while enterprise level information can be used to robustly validate modeled competitor performance. Current optimization methods on the other hand, focus on a single level predictive performance metrics (usually store turnovers).

Chapters 2, 3 and 4 explain in detail the novel aspects to understanding spatial consumer behaviour, SIM formulation, optimization and validation that have been discovered in pursuit of answering the above research questions. The ordering of the chapters follows the path of deeper study on certain store-choice dynamics discovered in earlier chapters. Notwithstanding the interdependency of the different chapters, each chapter can be read on its own.

Chapter 2 shows several extensions on the standard SIM formulation. In the store utility function, both a global brand strength indicator as well as a local brand presence factor are added next to the store's surface and store concept. On the demand side, a demand elasticity is modeled that depends on the level of local supply. When there are a lot of highly-attractive stores around, it triggers increased demand. Low-attraction local supply, in turn, can yield lower actual demand towards stores in favour of relevant substitutes.

A major contribution is made in regard to modeling interactions between consumers and different stores of the same retailer. The proposed SIM has been accommodated to better forecast the specific spatial store choice dynamics that come into play when a consumer is faced with the presence of multiple stores of the same retailer nearby. The proposed SIM is then able to forecast more accurately the sales cannibalization on existing stores when an opening of a new neighbouring store of the same retailer is simulated. Moreover, interaction penalties have been added to the SIM to accommodate for the different language areas that exist in Belgium. Subsequently, the extended SIM is applied to the Belgian food market. For the first time, validation data on three levels was gathered: Loyalty card information from a supermarket chain on customer origin level, store-level annual turnovers from the same retailer and enterprise-level annual turnovers for the entire food market (specifically for competitor estimation validation). The proposed highly non-linear model is optimized using Simulated Annealing, a meta-heuristic. While usually SIM's are optimized towards store-level accuracy, the optimization procedure used in this chapter explicitly looks for improvements on all three levels. Results show that the various extensions contribute to the accuracy of the SIM on multiple levels.

Chapter 3 elaborates on the concept of sales cannibalization by analyzing how stores of the same retailer compete spatially for the same consumers. The study uses customer origin data from six Belgian retailers selling different types of products to detect the varying role of two drivers for intra-network store choice: driving time towards a store and the size of its superordinate retail agglomeration. In a way, this research returns to the early days of retail location planning (1931) where Reilly [110] stated that the distance a consumer is willing to travel to a retail center is proportional to the center's size (Law of Retail Gravitation), but contributes to contemporary knowledge by looking specifically to store visiting preferences within the network of one retailer and by comparing these dynamics for different retailers across various product segments and location strategies. The aim of this study is to provide a methodology of spatial intra-network competition analysis where the results can be used to tailor the interaction component of the SIM more closely to observed customer behaviour.

Chapter 4 continues on the impact of retail agglomerations on store success and looks at the retail market from a more aggregated point-of-view: shopping areas (or retail agglomerations). A telephone survey of 16.000 consumers in Flanders inquiring on their shopping area choice is used to construct actual shopping area performance indicators. Moreover, the survey contains the surveyed consumers' appreciation of certain shopping area attributes. These qualitative attributes are then complemented with spatial configuration metrics of the shopping area borrowed from geography literature (for example, degree of store concentration). This set of qualitative and quantitative attributes is then used to explain the shopping area performance. While abundant research has been published on different drivers of store center success, it is rare to validate these drivers against actual performance information as argued in a recent paper by Dolega et al. [38]. This chapter also discerns different attribute impacts based on the typology of the shopping area: city centers, shopping malls and peripheral shopping strips. The results of this chapter can aid SIM formulation as it breaks the observed success of a retail agglomeration down to more specific underlying drivers that can be taken into account in an individual store's utility function.

Chapter 5 summarizes the research findings from this dissertation and elaborates further on the potential added value of an extended SIM for different stakeholders in the retailing process. The chapter is then completed with various suggestions for follow-up research.

2

A Robust Gravity Model for the Belgian Food Market[1]

2.1 Abstract

This study proposes a modified Huff model that takes directly into account spatial competition between stores of the same brand, brand attraction based on actual brand performance and spatially variable substitution. The model uses only publicly available or easily acquirable data as input, whereas model output is extensively validated on various levels. These levels include comparison of modeled and real market shares on block, store and brand level for the Belgian food market. Results show that multi-objective optimization of model parameters yields comparable results on block level to other models in the literature but improved results on store and brand levels, thereby ensuring model robustness. This robustness also enables the application of the model for various business purposes as store location determination, leaflet distribution optimization, store and store concept benchmarking, without loss of spatial generality.

2.2 Introduction

To monitor operational performance, retailers rely more and more on objective store benchmarks. Benchmarks are objective in a way that they quantify internal and external influ-

[1]Based on: De Beule M., Van den Poel D. & Van de Weghe, N.. *An extended huff-model for robustly benchmarking and predicting retail network performance*. Applied Geography 2014; 46(0): 80 —89.

ences on store performance (store size, brand, competition, geodemographic characteristics of consumers, etc.) to obtain a measure indicating the performance of the management. The more fine-grained such store benchmark is, based on for instance loyalty card information, the more targeted improvement actions can be defined. A store benchmark on a fine-grained block level is therefore more valuable than a benchmark on an aggregate store level for defining and monitoring the impact of marketing actions such as door-by-door leaflet drops. In expansion strategy, accurately predicting turnover for a new outlet is also of primary importance for today's retailers. An accurate turnover prediction can quickly indicate whether it is still worthwhile to pursue a scarce city center development opportunity or to accurately assess the opportunity cost on the future network of opening a new store outside the city center, where supply of potential location alternatives is still more abundant.

In the next sections, we propose a Huff-model that provides both a robust benchmark for current stores and an accurate turnover prediction for new stores, applied to the Belgian food market. In section 2.3, we explain in what ways our new approach extends the current state-of-art on store benchmarking and prediction techniques. Section 2.4 covers the development of the new model. In sections 2.5 and 2.6, we explain what data we use as input and validation data and how model performance is measured. In section 2.7, we discuss the performance of our model after optimization, both in comparison with other Huff-models and of the individual contribution to overall effectiveness of the model of the different model building blocks. Finally, in section 2.8, the results of this study are summarized and managerial implications and limitations for using this model in practice are discussed.

2.3 Literature and Own Approach

Many approaches to benchmarking and predicting turnover exist, ranging from simple methods as experience and analogs, over regression analyses to more complex methods as spatial interaction modeling and neural networks [140].

Already in 1964, Huff showed that gravity modeling techniques can have a significant contribution to solving these retail network management issues [66]. By calculating customer's probabilities for store patronage, the Huff model embodied an important milestone in scientifically assessing store trade areas. The model states that the market share of a store in a given region is proportional to the utility for consumers in this region generated by this store to the total utility generated by all stores in the neighbourhood of this region.

Ever since the formulation of the basic model in 1964, many extensions have been proposed to improve the predictive accuracy of this type of gravity model. Lakshmanan and Hansen [85] argued that a non-linear relationship between attraction and store size increases patronage prediction accuracy because the utility trade-off between store size and travel distance was now more flexible. Nakanishi and Cooper [97] proposed a strategy to estimate model parameters using ordinary least square estimations when a log transformation is applied to the different drivers of store attraction. Stanley and Sewall [125] added brand image to the attractiveness drivers of a store. Ghosh [54] was the first to account for spatial non-stationarity of the parameters used in a gravity model, because the relevance and impact of different drivers of store attractiveness can vary across geographic regions. Orpana and Lampinen [101] introduced different store concepts in the gravity model based on the size of grocery stores. A separate set of parameters for each store concept was estimated to model the varying impact of store attractiveness drivers on each store concept as they serve a different shopping purpose.

Next to finding the right drivers and estimation procedures, many applications of the Huff model have been proposed and tested in literature. These applications include university campus selection [23], store selection in the furniture market [29], the choice of movie theater [34], and the analysis of spatial access to health services [137, 138]. The most common application in both literature and practice however, is found in the grocery market, since it is one of the most saturated markets, for which benchmarking and a predictive model is most valuable.

We argue that in current approaches proposed in the literature several shortcomings can be found. First, we have found very few research that looked into the impact of the spatial configuration of the store networks and, more specifically, that looked to how the presence of multiple stores of the same retail chain in a customer's choice set can influence store performance in that area. Secondly, we notice a lack of variety of information used to validate the proposed models. This is mainly due to the fact that most, if not all, papers focus solely on answering one management issue. For example, Orpana and Lampinen [101], Li and Liu [90], and Sandikcioglu et al. [117] focused solely on the prediction accuracy for retail locations. For this purpose they use only information on a store level, which yielded good results for their purpose. Less research has been conducted on block level, based on questionnaires or loyalty card information. Gauri et al. [51] use such block level information and gravity modeling techniques for a store performance benchmark exercise. Although the results on block level for the performance benchmark were good, the results on a more aggregate store level were less satisfactory. None of the existing work on gravity modeling has incorporated results on a higher level, the food retail chain, despite being readily available in a nation's database of financial statements. A final shortcoming can be found in the type of input data used in existing gravity models. Collecting a wide variety of input data to capture more influencing factors [69] can be extremely time consuming or very costly when bought. Retailers are therefore often reluctant to acquire these data because the marginal benefit of incorporating these data in practice has become questionable. In this chapter, we show how easily available information can be used for maximum applicability and results in practice, ensuring high return on investment.

This chapter aims at constructing a robust gravity model for the whole Belgian grocery market, using an extensive set of easy-to-gather input and validation data. In doing so, we address the three aforementioned shortcomings. First, the state of art of the Huff-model is extended by incorporating more spatially influencing factors, such as brand recognition and internal cannibalization of sales between stores of the retail chain. The inclusion of such factors can provide valuable insights in a retail chain's network expansion strategy. Secondly, block level information drawn from a grocery retailer's Customer Relationship Management database is used in addition to annual store turnovers from the same grocery retailer and annually reported group turnovers for all competitors as reported in their financial statements. Validation on these three levels is applied for an improved robustness of the proposed model. Lastly, in our approach, only easy-to-gather input data on a national scale is used. Therefore, we limit our model to the store surface and the store brand as a measure of store attractiveness. Addresses and brands of stores can easily be acquired using company websites and common knowledge of the competitive landscape. While calculating surfaces on a large scale can be time consuming, the spread of freely accessible aerial photographs (Google Earth, Bing Maps) [90] and more detailed socio-economic permits have sped up its calculation considerably.

2.4 Model Development

Starting from the basic Huff model, this section explains the extensions that seek to improve predictive and benchmarking accuracy on block, store and chain level.

Basic Huff model

As a starting point for our model we use the Huff model as proposed in 1964. It states that the patronage probability P_{ij} of a store j for inhabitants and workers in a given region i (henceforth named 'residents of block i') is equal to the proportional utility of this store (U_{ij}) compared to the total utility generated by all N stores in the neighbourhood of this region:

$$P_{ij} = \frac{U_{ij}}{\sum_{q=1}^{N} U_{iq}} \tag{2.1}$$

The utility generated by grocery store j for residents of block i is calculated as:

$$U_{ij} = \frac{A_j}{{D_{ij}}^{\beta}} \tag{2.2}$$

The value A_j represents the aspatial attractiveness component for store j. In the basic Huff model, store size is used for A_j. As mentioned in section 1.2.2.2, it is however possible to incorporate more drivers for aspatial store attractiveness by averaging or multiplying different drivers. D_{ij} is the distance between store j and the centroid of block i. In most research, Euclidian distance based travel times are used. However, with recent technology advances, the calculation of fastest route travel times has become feasible, even for large scale projects. The parameter β shows the relationship between distance and attractiveness of the store.

To translate probabilities from formula 2.1 into monetary allocations, it is assumed that the total spending potential of a block is divided evenly according to the store visit probabilities P_{ij} for all stores j in close proximity.

$$F_{ij} = P_{ij} \cdot SP_i \tag{2.3}$$

Where F_{ij} equals the monetary flow between store j, and block i and SP_i is the total spending potential on groceries of all residents of block i.

Extending the Huff model
Taking the above basic formulation as a starting point, we now further develop this model to incorporate more influencing factors on store choice probabilities. The development of the model is explained in three phases. In the first phase, an Unrelated Total Attraction (UTA_{ij}) for every block i in regard to store j is calculated. In the next phase, UTA_{ij} is modified to account for weakening and fortifying effects of regional brand presence, resulting in a Related Total Attraction (RTA_{ij}). Finally, after incorporating substitution for grocery spending in grocery stores in the model, store visit probabilities are calculated using the Related Total Attraction. The resulting monetary allocations then can be validated with real sales information.

Phase 1: the construction of UTA_{ij}

S_j **- Store size**

Larger stores carry a more complete and voluminous range of grocery products. More choice options and a better product availability tends to be more attractive to consumers.

BA_{b_j} **- Brand Attraction**

Another important influencing factor on store choice is the brand each grocery store belongs to, as each grocery store chain has its own store format. Incorporating a brand related attraction value in the model thereby reflects two influencing factors: shelve density and attraction of the brand format to consumers. Although store size is an adequate proxy for the range of products carried, the different store formats have varying shelve densities, resulting in fluctuating sales per square meter. The incorporation of such a brand attraction measure can then refine the impact of store size on store attractiveness. Also, due to pricing and/or product strategy differences, some grocery store chains are more attractive to consumers than others. Using the global turnover results of each grocery store chain and the total surface of their stores in Belgium, an average annual turnover per square meter, BA_{b_j}, can be calculated, which is a good relative approximation of the attractiveness of the brand concept b_j, independent of the store j's size. For a market entrant the application of this approach is difficult, as they haven't realized any turnover yet. This can however be overcome by using the same BA as an existing firm following a similar strategy.

LB_{ij} **- Language Borders**

Belgium is characterized by its division in three major geodemographic areas: Flanders, Brussels and Wallonia. In Flanders the mother tongue is Dutch, while the native language in Wallonia is French. Finally, Brussels is characterized by both Dutch and French speakers. Due to these language borders, there is a preference for most people to shop only in their own geodemographic area. To model these geodemographic borders, penalties for cross-border utility calculations are calculated, according to which specific geodemographic border is crossed (Figure 2.1). These penalty values have been estimated based on expert interviews. A penalty of 0.1 corresponds for example with a 90% reduction of the store attractiveness. Moreover, since the majority of the focal brand's stores are located in the southern part of Belgium, we also took French grocery stores close to the Belgian border into account. These cross-nation allocations are also subject to a penalty according to the language of the resident of a block and the area in which the store is located.

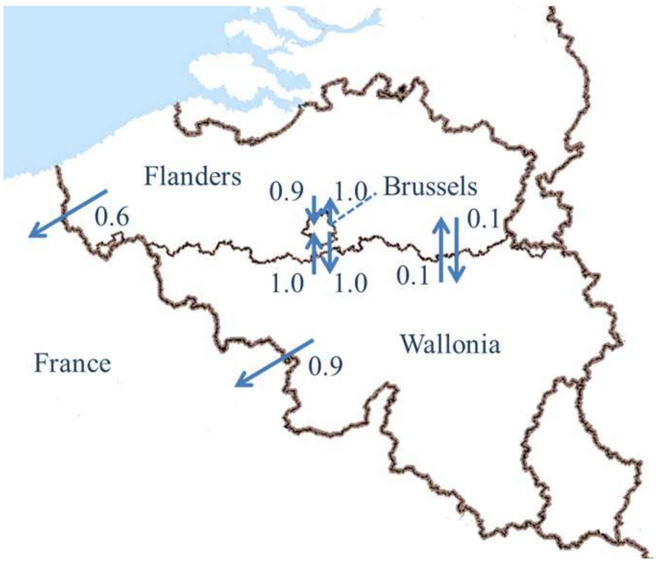

Figure 2.1: Graphical depiction of the attraction multipliers across geodemographic borders.

K_j **- Grocery Store Concepts**

Different store concepts also have spatial differences in attraction. Hypermarkets are characterized by the largest store surfaces in the grocery market and usually have the largest parking spaces. From a spatial point of view, it significantly increases the fixed time cost of visiting this type of store concept. From an aspatial point of view, they also carry the most complete range of grocery products, as covered in brand attraction and store surface. This store configuration tends to be more attractive to consumers from distant areas, who prefer large quantity one-stop shopping trips, thereby reducing the relative impact of the larger fixed time costs on the total time cost of their shopping trips. For residents at closer dis-

Sales surface	Store concept
$< 400\, m^2$	Local grocery store
$\geq 400\, m^2$ and $< 2,500\, m^2$	Supermarket
$\geq 2,500\, m^2$	Hypermarket

Table 2.1: Different store concepts used.

tances however, the impact of the higher fixed time costs is often too high for top-up shopping trips, which reduces the relative attractiveness of these hypermarkets for consumers at closer distances. Local shops are characterized by the inverse relative attractiveness. They are very attractive for local residents for quick top-up shopping, while being less attractive to more distant residents as their limited range of products prevents a time-equitable one-stop shopping trip. To model these spatial differences in attractiveness between different store concept, we divide the grocery stores in scope into three categories: local grocery stores, supermarkets and hypermarkets. For each of these grocery store concepts, separate travel-time dependent parameters are introduced. Table 2.1 presents the classification as proposed by Orpana and Lampinen [101], which is also used in this study.

Also, a fourth store concept is introduced for the retailer who provided the sales data, both loyalty card information and store turnovers. This choice is motivated by the possibility these sales data offer to model their specific market dynamics more accurately than brands for whom we have only sales data on brand level, while avoiding overfitting for these other brands. When using this model for another retailer, it also means the model has to be re-estimated using their specific data.

To accurately model these differences in spatial attractiveness, we introduce both a global attractiveness parameter SC and a distance related parameter DP for every store concept k_j:

SC_{k_j} **- Global impact of store concepts**

The typology of store concept has a fixed influence on the incurred time cost. Other researchers have also implemented these ideas, either implicitly or explicitly: Pauler et al. [103] and Gauri et al. [51] augment the Euclidian distance between consumers and grocery stores by a fixed increment, thereby implicitly accounting for a fixed time cost. Orpana and Lampinen [101] also add a fixed time increment to the distance function. We propose a similar modification in the distance function specification which also accounts for an incurred fix time cost. Panel A of Figure 2.2 shows such a classic Huff distance-attraction decay with a fixed time penalty. In literature, many other forms of distance-attraction decay have been proposed [83]. In this study, an exponential relationship is used: $SC_{k_j}/exp(D_{ij} * DP_{k_j})$. For every store concept k_j, parameter SC_{k_j} will indicate the relative fixed time cost increment, as shown in panel B of Figure 2.2.

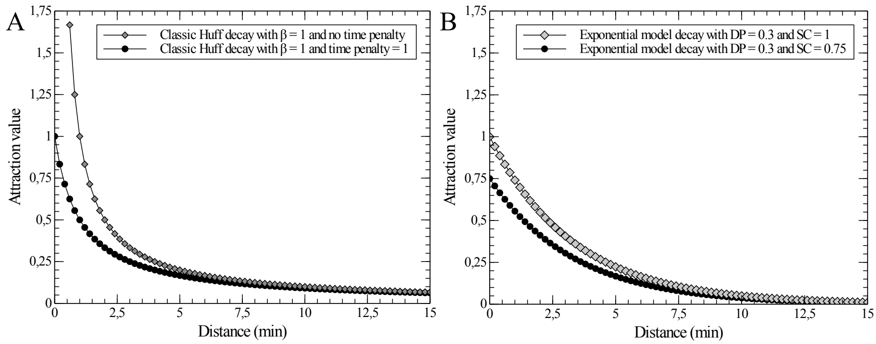

Figure 2.2: Comparison between classic Huff decay with time penalty and the Huff decay proposed in this study.

DP_{k_j} **- The impact of distance**

We measured the distance between customers and stores as the average between Euclidian distance based travel time and fastest route travel time, since customers not judge only the spatial attractiveness of a store on the travel time of the fastest route but on geographical proximity as well. We refer to section 2.7 for a proof of the contribution of this approach to the overall effectiveness of the model.
Parameter DP_{k_j}, combined with the fixed time cost parameter SC_{k_j}, determine the time-dependent attraction of each store concept. Figure 2.3 shows a distance-attraction relation for each store concept. Independent of their surface, a local grocery store has greater local attraction then any of the other store concepts, while a hypermarket has greater attraction on longer distances.

Combining the previous drivers of store attractiveness, we can now calculate the Unrelated Total Attraction of every grocery store j close to block i:

$$UTA_{ij} = \frac{S_j \cdot BA_{b_j} \cdot LB_{ij} \cdot SC_{k_j}}{e^{D_{ij} \cdot DP_{k_j}}} \tag{2.4}$$

The Unrelated Total Attraction of every grocery store j for block i is thus directly proportional to the average turnover of a store from brand b_j with surface S_j weighted by language border penalties LB_{ij} and the store concept impact SC_{k_j} and inversely proportional to an increasing function of the distance to the store D_{ij}.

Phase 2: the calculation of RTA_{ij}

The presence of stores of the same brand in a region can have both fortifying and weakening effects on the attractiveness of a grocery store. First of all, the biggest competitors of a grocery store that is part of a chain are neighbouring stores of the same chain. While the

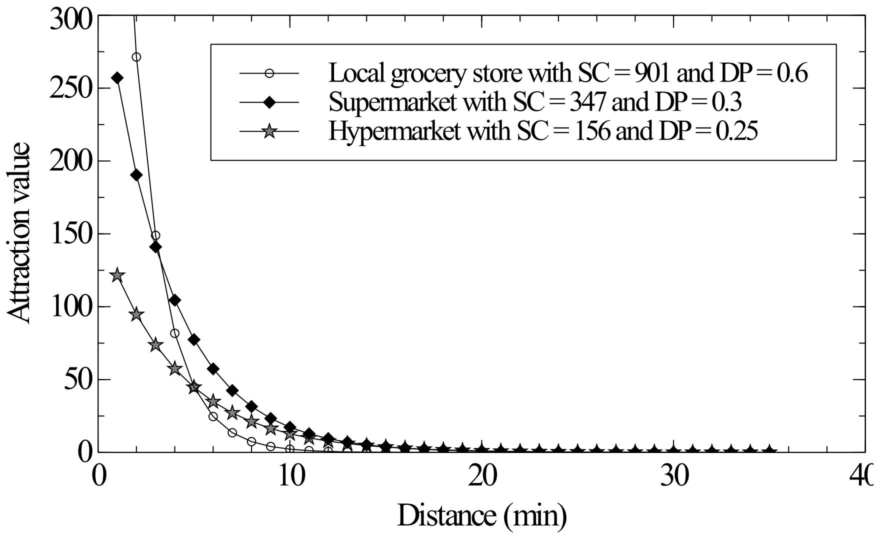

Figure 2.3: The distance-attraction relationship for each store concept. The values for SC and DP were chosen based on the optimal solution obtained in the results section.

Huff model takes competition between stores of different brands directly into account in the utility values, it is not as accurately accommodated to take competition within a brand into account. If, for example, for a certain geographic area, two grocery stores of different brands are in scope, customers will divide their purchases according to the stores' respective attractiveness values. This division is however much more unlikely if the stores belong to the same brand. In this situation, the store with the highest attractiveness is likely to attract more than its share attributed by a classic Huff model, because both stores are almost perfect substitutes and rational consumers will virtually only visit the store providing them with the highest utility. Therefore, we attribute a penalty to all but the most attractive stores per brand in the eyes of the residents of every region.
This penalty is calculated as follows:

$$CF_{k_j}^{\left(\frac{\sum_{q|b_q=b_j, UTA_{iq}>UTA_{ij}} UTA_{iq}}{UTA_{ij}}\right)} \tag{2.5}$$

Where CF_{k_j} ($0 \leq CF_{k_j} \leq 1$) is a cannibalization penalty factor and is a parameter that will be estimated per store concept k. The power to which CF_{k_j} is raised depends on the ratio between the Unrelated Total Attraction of more attractive stores of the same brand for residents of region i and store j's Unrelated Total Attraction. A similar approach was used by Kaufmann and Rangan [73], who developed a model for site location for a franchise company. In this model, they argue that customers choose the franchisee that provides them the highest utility among all other available franchisees. Such an approach can be achieved in our model when CF_{k_j} approaches zero. When CF_{k_j} is 1, the classic Huff model is attained. A similar notion is used by Wan et al. [138] for correctly determining the demand for health services. In the proposed three-step floating catchment area (3SFCA) method, the demand for health services provided by a medical facility is also cannibalized by the presence of other facilities in closer proximity to a block.

At the same time, the presence of multiple stores of the same brand in close proximity has a reinforcing effect on the attractiveness of all of these stores. Naert and Bultez [96] argued that a logistic 'S' relationship exists between market share per store and the number of stores of the same brand in geographic proximity. When opening a first store in a region, consumers are not yet familiar with the format of the chain. The more stores of the brand that have opened in the region, the more familiar consumers become with the concept, hence the increased market share per store. Naturally, with an even larger increase in numbers, the marginal effects of an additional store start to decrease.

The brand presence BP_{ib_j} of a brand b_j for block i is calculated as follows:

$$BP_{ib_j} = 1 + BPF \cdot BPS_{ib_j} \tag{2.6}$$

where BPS_{ib_j} is defined as the relative share of grocery stores of brand b_j for every geographic block i and BPF is a parameter optimizing the impact of the brand presence. The relative share of grocery stores of brand b_j for block i is calculated as the number of stores of brand b_j within a 20 minute travel time radius on the total number of stores within the same time radius. As Figure 2.4 indicates, the BPS factor for the focal retailer is zero for the majority of blocks, since its network contains only 61 stores. Furthermore, the maximum BPS of 25% -meaning that 1 in 4 grocery markets within 20 minutes of these blocks belong to the focal retailer- indicates high local concentrations of focal stores.

When comparing Figure 2.5A with 2.5B, it is clear that brand presence has reinforced the individual attraction of each of both stores in close proximity to the store, while for the zones in between both stores, where the internal cannibalization is the strongest, the clear preference for one of both stores has weakened the aggregated attraction of both stores.

By taking these factors into account, the Independence of Irrelevant Alternatives (IIA) property from the classic Huff model, does not longer apply. The IIA property states that the ratio of the probabilities of an individual selecting two alternative stores is unaffected by the addition of a third alternative store [142]. In our model, the introduction of a new alternative effectively influences the relative preferences of existing choice options when taking brand into account, as fortifying and weakening effects of brand presence will also influence the attractiveness of existing store options.

With these fortifying and weakening effects of brand presence, we can now calculate the Related Total Attraction of every store j close to block i:

$$RTA_{ij} = BP_{ib_j} \cdot UTA_{ij} \cdot CF_{k_j}^{\left(\frac{\sum_{q|b_q=b_j, UTA_{iq}>UTA_{ij}} UTA_{iq}}{UTA_{ij}}\right)} \tag{2.7}$$

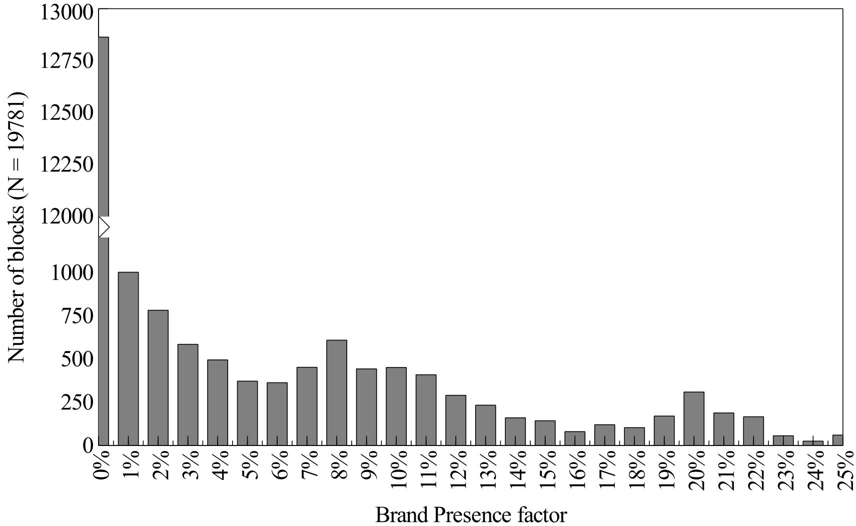

Figure 2.4: The spread of Brand Presence factors for the focal retailer for all geodemographic blocks.

Phase 3: The calculation of the store visit probabilities.

In this final phase, we transform the Related Total Attraction values to store visit probabilities and finally to monetary allocations.
It is however highly unlikely that all of the grocery budget within a family will be allocated to the grocery stores in our database. Substitution is often triggered by the absence of close grocery stores or by servitized alternatives like restaurants. Therefore, we incorporate two parameters FS and RS that model these two substitution possibilities when calculating store visit probabilities P_{ij} (see Equation 2.8). FS reflects a fixed attraction to substitutes regardless of any region specific characteristics. If there are abundant grocery stores in close proximity, i.e. large aggregated RTA values, much of the potential demand will be triggered. This is reflected in the fact that FS will be relatively small compared to $\sum_{q=1}^{N} RTA_{iq}$ and substitution thus will be minimal. Servitized substitution alternatives are more likely to be located in densely populated areas. Therefore, we multiply the population density PD_i in region i with a parameter RS to obtain a measure of servitized substitution.

$$P_{ij} = \frac{RTA_{ij}}{(\sum_{q=1}^{N} RTA_{iq}) + FS + RS \cdot PD_i} \tag{2.8}$$

Finally monetary allocations can be calculated using equation 2.3:

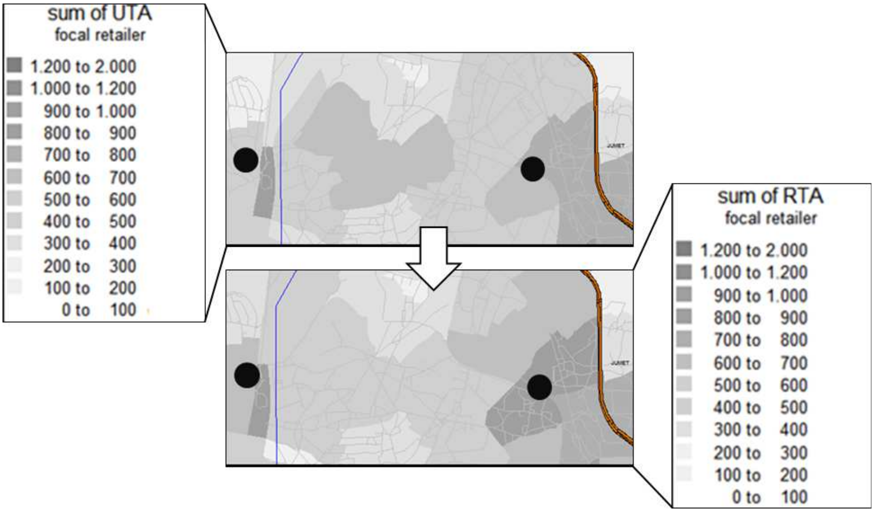

Figure 2.5: The aggregated Unrelated and Related Total Attraction values per geographic block for 2 stores of the focal retailer.

$$F_{ij} = P_{ij} \cdot SP_i \cdot PM \tag{2.9}$$

Where PM is a potential multiplier used to fine-tune the spending potential figures SP_i we pre-calculated.

After obtaining all allocations, aggregations can be made to obtain results on store and brand level. Figure 2.6 shows such an aggregation for the focal retailer. Comparison with true allocations on block level or turnovers on store level is then the basis of model optimization.

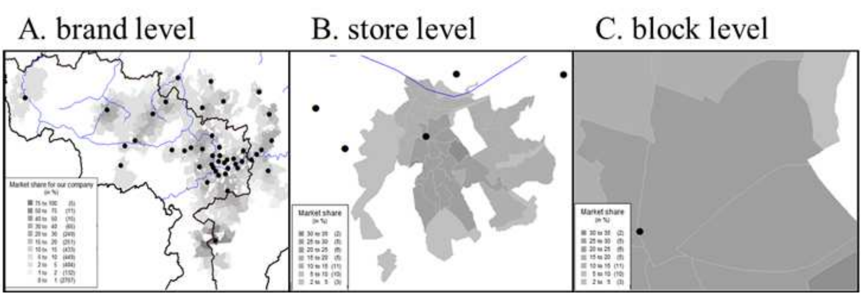

Figure 2.6: Graphical depiction of the three benchmarking levels.

2.5 Test Design

Solution procedure

Due to the non-linear nature of the proposed model, linear regression techniques for parameter optimization cannot be applied. Optimization techniques that are capable of dealing with such highly complex non-linear optimization problems, are for example meta-heuristics. They however cannot ensure an optimal solution. We opted for a simulated annealing (SA) solution procedure, which is part of the descent family of meta-heuristics. Simulated Annealing was introduced in 1983 by Kirkpatrick et al. as a probabilistic solution method capable of finding very good results in limited computing time. It is also commonly used as a multiobjective optimization strategy [127]. The use of validation data on different levels allows for a multiobjective optimization and provides a robust model. When optimizing a multiobjective optimization problem, a set of pareto-optimal solutions is obtained. Pareto-optimal solutions are solutions for which there exists no feasible solution that equals or outperforms this solution on all criteria of the multiobjective optimization problem, in this case the MAPE on block, store and brand level. However, it needs to be pointed out that an intelligent steering of the SA procedure for this problem formulation is very difficult. The highly complex definition of the problem makes a neighbourhood definition around an accepted solution very difficult to define. In order to use the benefits of the SA intelligence to its best, the control of the deterioration acceptance for temporary solutions was controlled on store level, having stabler neighbourhoods than the more fine-grained block level, while allowing for better parameter fitting than the more aggregated brand level. To ensure good results within reasonable time however, we opted for a standard multiobjective simulated annealing (MOSA) procedure with slow temperature decrease and allowed the search procedure 10.000 iterations to calibrate the optimization parameters.

Performance benchmarks

The quality of the proposed model is evaluated in comparison to a classic Huff model and an extended Huff model found in literature that was applicable to our dataset. Benchmarking with other models in the literature has indeed proven to be very difficult, since most papers work with a very broad range of input data, which are often not available or not relevant outside their test environment. A first benchmark is made with the basic Huff model as proposed by Huff (see equation 2.2). Model M1 of the extended Huff model proposed by Orpana and Lampinen [101] is also tested:

$$U_{ij} = SC_{k_j} \cdot {S_j}^{\alpha_{k_j}} \cdot D_{ij}^{\beta_{k_j}} \tag{2.10}$$

where the number of store concepts j is only 3, compared to 4 in our model.

As a performance measure on all 3 levels, the Mean Absolute Percentage Error (MAPE) is calculated:

$$MAPE = \frac{1}{N} \sum_{n=1}^{N} \frac{|O_n - M_n|}{O_n} \tag{2.11}$$

Where N is the number of observations depending on the level of the validation data (block, store or brand level). O_n is the true observed result for area n, while M_n is the modeled result for area n (if on block level, $M_n = F_{ij}$). For more comparative results, the pseudo R^2 fit measure, used by Gauri et al. [51], is also reported:

$$Pseudo\, R^2 = \frac{var(O(MS_n)) - var(\epsilon_n)}{var(O(MS_n))} \tag{2.12}$$

Where $O(MS_n)$ is the observed market share for area n (block, store or brand level) and $\epsilon_n = O(MS_n) - E(MS_n)$ where $E(MS_n)$ is the expected market share in area n according to the model. This fit measure thus indicates how much of the observed variance is explained by the model. However, since we are unable to use regression techniques and have opted for a meta-heuristic, $E(\epsilon_n) \neq 0$. If optimized towards this performance measure, robustness of the solution cannot be guaranteed as skewness in the results cannot be prevented. To still ensure comparable results, we added a 6% deviation constraint to the mean percentage deviation of the results on store level. Due to the limited number of observations on brand level, the pseudo R^2 will be reported only on block and store level. To avoid overfitting, we subdivided the allocations on block level into a 2/3 training and a 1/3 validation set. We did not opt for a test and validation set on store and brand level, given the limited number of observations.

Calculation performance improvements

Because of the scale of this research, calculation time per iteration can be quite long. To reduce the calculative burden, we added constraints on how many stores are evaluated per block. Indeed, it can be assumed that from a certain number of stores on, the true allocations of spending potential become negligible. We fixed this number on the 18 closest local grocery stores and supermarkets and the 2 closest hypermarkets. Preliminary evidence showed that this number yielded sufficiently accurate results while maintaining acceptable calculation times.

2.6 Data

The proposed model was tested on a national scale. For this purpose, an inventory of grocery stores in Belgium was fetched. For ease of gathering this information, only grocery stores belonging to a food chain were added, provided that the food chain had at least seven grocery stores in Belgium. This process yielded a database with 3,420 grocery stores, belonging to 34 food chains. To complete this database, we added net sales surfaces of these grocery stores. Due to the availability of high resolution aerial photographs it is much easier to accurately estimate sales surfaces of stores. This process is for example used by Li and Liu [90]. Next, we obtained annual sales data from a major food retailer in Belgium for the year 2010. For 61 (out of 63) supermarkets (with surfaces between $600m^2$ and $2,400m^2$) we obtained loyalty card information. After geocoding the addresses, the annual sales quantities were allocated to the different blocks in Belgium. This aggregation resulted in 27,143 monetary allocations from geographic blocks in Belgium to the 61 stores for which loyalty card information was available. Since not every transaction is logged with a loyalty card, the current spread of sales registered with loyalty cards is corrected to obtain the complete annual turnover for every store. From the National Institute for Statistics, we obtained geodemographic information on the 19,781 geographic blocks in Belgium. Taking the number of families and the average revenue of each block into account, a partial expenditure potential on groceries was calculated. This potential was further augmented with an expenditure potential of the total workforce active in each block, since they too are prone to buy groceries before, after or during their stay at their workplace. This resulted in a total expenditure potential per block i, SP_i. Since the expenditure potentials are indications, parameter PM was introduced in the model to fine-tune the global expenditure potential. Fastest route driving times were calculated from the center of the geographic block to the exact location of the store using Microsoft MapPoint Europe 2011.

2.7 Results

In this section, the results of a 10,000 iteration optimization run are presented. In the first paragraph, we discuss the optimized parameters and compare the results with the performance of other gravity models from literature on our dataset. In the second paragraph, we perform iterative sensitivity analyses to measure the contribution of several proposed drivers of store attractiveness to the overall performance of the model.

Comparative results

Table 2.2 shows the optimized parameters for each tested model after a 10,000 iterations optimization run. Due to the fact that substitution was explicitly taken into account in our model, the potential multiplier PM is higher compared to the other models as part of the market is not allocated to stores in our database. The store concept multipliers SC are both used in our model and the M1 model of Orpana and Lampinen. The difference in absolute magnitude of the parameter values between both models is not important as store visit probabilities are calculated, which involves a relative weighting of attraction scores (see equation 2.1). The relative difference in parameter value between store concepts however, is much more important and is relatively comparable between both models, indicating the same capture of store concept dynamics. This finding is also confirmed when looking to the distance related parameters DP for our model and β for the other 2 models: the larger the store concept, the lower the impact of distance becomes. Moreover, in our model the impact of distance for our focal retailer is larger than for a comparable supermarket, indicating the somewhat more 'local store' image of the focal retailer. To correctly interpret the resulting cannibalization factors CF, one has to take the varying impact of distance for different store concepts into account. For local stores, having very small trade areas, it is much more difficult to accurately assess internal cannibalization as it is not so common that their trade areas converge. The bigger the stores become however, the more the trade areas of stores of the same branch are likely to converge and internal cannibalization becomes more important, hence the increasing penalty values for bigger store concepts.

Parameter		Our model	Basic Huff	M1
Name	Store concept			
FS	-	570	-	-
SF	-	0.0798	-	-
PM	-	0.94	0.6	0.6
BPF	-	2.1	-	-
SC	1	901	-	8
	2	347	-	4
	3	156	-	2
	4	347	-	-
DP/β	1	0.6	2	3.2
	2	0.3	-	3
	3	0.25	-	2
	4	0.4	-	-
CF	1	0.6	-	-
	2	0.35	-	-
	3	0.2	-	-
	4	0.6	-	-
α	1	-	-	0.7
	2	-	-	1
	3	-	-	1

Table 2.2: Parameters of the best solutions found.

Results from Table 2.3 show that our proposed model outperforms the basic Huff model significantly on all performance measures, although our model uses only global brand results as additional input data. This also indicates that the complex non-linear relationships in our model result in significant improvements in overall accuracy. More specifically, a 66.4% mean absolute percent error was found on the test set on block level, whereas the validation set confirmed this result with a MAPE of 62.99%. The performance measures on block level result in relatively high mean absolute percentage errors, especially compared to the MAPE on store level. Since we did not trim the observed allocations, every observed allocation that did not have a modeled counterpart (or vice versa) resulted in a 100% deviation for that block. When taking only the 500 biggest allocations into account, we see a remarkable decrease in MAPE on block level to 37%. Since these minor allocations have a relatively small impact on store level, the mean absolute percentage error on store level drops significantly to 22.34%. On brand level a MAPE of 22.28% was found, which is very satisfactory given the fixed nature of the Brand Attractions. Furthermore, a nearly 50% increase in explanatory power of the model compared to the basic Huff model is found when looking at the pseudo R^2. Our model explains 76% of the variance in market share on block level, which is in line with the results of Gauri et al. [51]. When looking at the M1 model of Orpana and Lampinen, it also outperforms the basic Huff model on all levels, thanks to the addition of parameters on store concept level. Compared to our model, results are comparable on block level, while our model outperforms the M1 model on store level, indicating that the addition of extra spatial or brand related attractiveness drivers in our model have improved accuracy on store level. Finally, the addition of Brand Attraction indicators for each brand in our model clearly benefits the result on brand level, thereby also drastically improving model robustness when for instance testing a potential store location in this competitive landscape.

Level	Block			Store	Brand
Performance measure	MAPE		R^2	MAPE	MAPE
Set	Test	Validation	Complete	Complete	Complete
Our model	66.40%	62.99%	76.11%	22.34%	22.28%
Basic Huff	117.48%	115.66%	26.47%	35.17%	57.36%
M1 Orpana and Lampinen [101]	66.19%	58.23%	71.56%	26.78%	47.78%

Table 2.3: Comparative results

Figure 2.7 shows the distribution of the 63 focal stores according to their percentage error. The maximum absolute error for one store was 66%. For all other stores the absolute percentage error was contained within 50%. Compared with other results in literature, this is a very solid outcome. Although comparison between two different geographic regions is difficult, our model returns for instance a modeled store turnover for 98.41% of the focal stores within a 50% deviation from their real turnover while the Store Performance Index presented by Gauri et al. [51] yields modeled store turnovers of approximately 85% of the focal stores within a 50% deviation from their real turnover. From a practical point of view, these deviations can be discussed with store management to improve performance or learn best practices. For simulation purposes, these figures however indicate that individual on-the-field insight in each case is necessary for an even more accurate prediction.

Sensitivity analysis

Next to comparative results, we also measured the impact of the different newly proposed attractiveness drivers on the total performance of the model. We iteratively dropped or changed one of the model building blocks to measure the drop in model accuracy. Table 2.4 shows the optimization results after 10,000 iterations. For generality reasons, we did not test the impact of language border penalties since it is a specific Belgian characteristic. On block level, we noticed no clear evidence with the MAPE measure of contribution to overall effectiveness in all sensitivity tests. However, the R^2 measure indicates that the contribution of brand attraction, internal cannibalization and the combination of real and Euclidian distance based travel times are significant. The improvement with the incorporation of brand presence on block level is rather small, as was also noticed when comparing our model to the M1 model of Orpana and Lampinen [101], but can be explained recalling

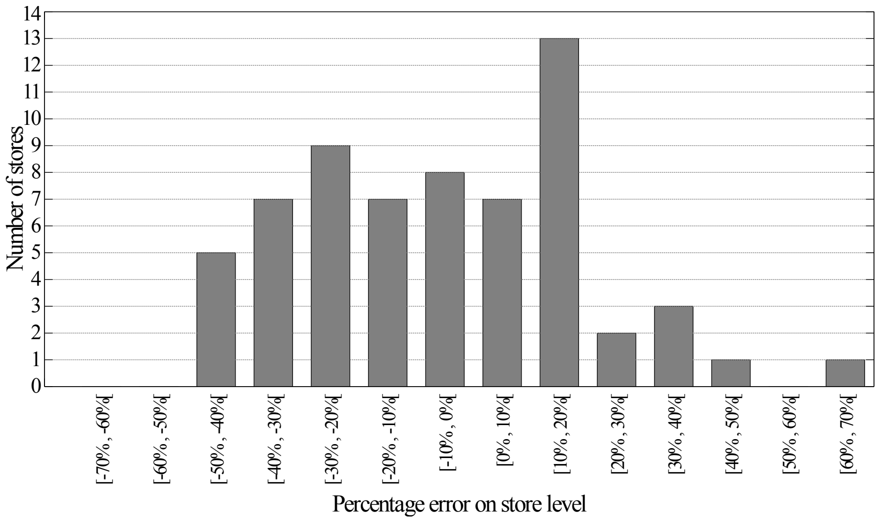

Figure 2.7: Distribution of percentage errors on store level

Figure 2.4, as it has a significant impact on few blocks with high brand presence.

Looking at store level results, we noticed a decrease in error terms in all six test cases. Small deteriorations are found when dropping brand attraction and brand presence drivers. The limited effect on brand attraction is due to the fact that the focal retailer has its own store concept, for which SC_{k_j} is now optimized to act as a brand attraction driver for the focal retailer. Brand presence in turn, has only a small spatial impact due to the focal retailer's specific network configuration, as shown in Figure 2.4, but has a strong local impact in the few areas with high brand presence. The most significant decrease in predictive error is found in the use of hybrid travel times. Figure 2.8 shows the accumulated turnover for blocks located at a certain travel time (x-axis) to the stores for whom we have loyalty card information. From these graphs it is clear that that our proposed model closely matches the real sales from a spatial point of view. Using solely Euclidian distance based travel times however, is clearly not as capable to capture the spatial dynamics in the market, specifically at shorter distances. Using fastest route travel times, on the other hand, enables accurate modeling at shorter distances while it fails to do so at longer distances. Using hybrid travel times significantly mitigates the shortcomings of both approaches.

Finally, on brand level, the deterioration caused by dropping Brand Attraction is significant, as expected. Dropping other drivers has only marginal effects on brand level, except for the moderate influence of Internal Cannibalization, which indicates that it is an important concept to take into account when modeling a whole market segment.

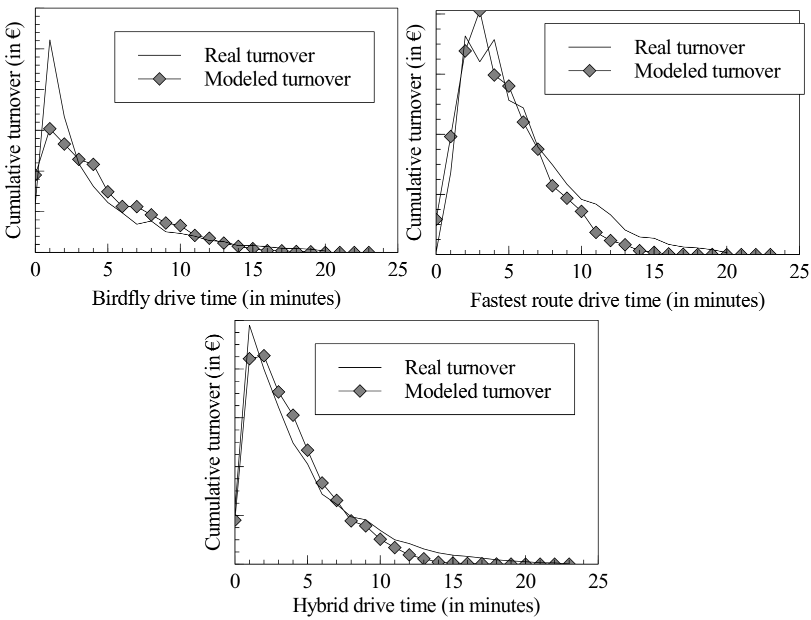

Figure 2.8: Comparison between modeled and true turnover for every minute driving time using different driving time calculations.

Level	Block			Store	Brand
Performance measure	MAPE		R^2	MAPE	MAPE
Set	Test	Validation	Complete	Complete	Complete
Our model	66.40%	62.99%	76.11%	22.34%	22.28%
Dropping Brand Attraction	67.68%	64.72%	71.90%	22.96%	41.47%
Using Euclidian distance based travel times	65.52%	71.90%	60.20%	25.91%	23.56%
Using Fastest route travel times	63.29%	61.52%	75.45%	23.12%	25.89%
Dropping Internal Cannibalization	60.68%	65.70%	72.87%	23.51%	28.34%
Dropping Brand Presence	61.27%	65.12%	76.05%	23.01%	22.27%

Table 2.4: Sensitivity analysis on model building blocks

2.8 Managerial Implications, Limitations and Suggestions for Future Research

We showed that starting from a limited variety of input data that are easy to acquire, a robust multi-purpose gravity model with high accuracy can be formulated. Moreover, for the first time a gravity model has been validated on three different levels: block, store and brand level. On all three levels the results clearly indicate the benefit of our proposed model compared to a standard gravity model and models previously proposed in literature. More precisely, we showed that incorporating both spatial and aspatial brand related drivers of store attractiveness have a significant positive impact on predictive accuracy for a focal retailer.

The model can be used for multiple purposes in practice. The deviations on block level can be discussed with the management, and targeted actions can be defined. On a more aggregate leve, the store level, we see that the predictive accuracy is very satisfactory. Such predictive accuracy can be used for predicting turnover of a new location and, especially for our model, for accurately predicting the impact on existing stores. Although a gravity model can rapidly indicate potential turnovers and impacts on current networks, it still must be used with caution. Although we believe we have captured the most important drivers of store success in the model - except for difficult to capture drivers as store management- many more drivers have an influence on store success. Therefore, a model can never replace a visit on site as it will provide many more insights in the choice behaviour of local consumers [140].

The aim of a model should then not be to act as a final predictor, but as an effective funneling instrument to filter sets of potential locations, as shown in Figure 2.9.

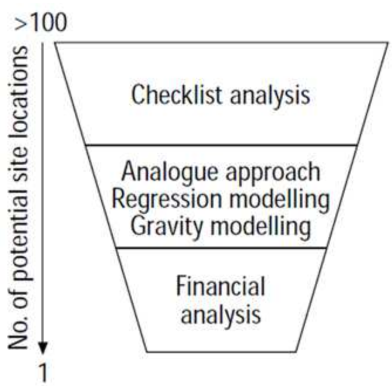

Figure 2.9: The process of retail location assessment. Reprinted from Clarkson et al. [28]

This chapter therefore aims to provide a valuable, robust starting point for retailers in their attempt to formulate a good predictive and benchmarking model. Augmenting the model with more elaborate and relevant data will virtually always contribute to an increased model accuracy and should thus be encouraged. In order to deepen the impact of brands on individual store results even further, it is for instance worthwhile looking into geodemographic segmentation of the population to model the targeted population groups of the different retailers [57]. Also, a more extensive validation based on detailed results on block and store level from multiple retailers across multiple store concepts can increase model robustness and generalization. Finally, as pointed out in section 2.5, an intelligent optimization procedure is very difficult to configure for the highly complex formulation of the model. Limited intelligence was introduced in our optimization due to very difficult neighbourhood definitions. Although the used procedure yielded satisfactory results on all levels, it cannot be assured the optimal solution was found, and a better solution still can be found using an improved optimization methodology.

3

Spatial Competition within a Retail Network[1]

3.1 Abstract

This study investigates the impact of driving time and retail agglomerations on consumer store choice within a retail network. A pairwise comparison of confluencing store trade areas is conducted based on loyalty card information and exit questionnaires for six retailers operating in different product categories in Belgium. Results show that there is a stronger emphasis in the preference hierarchy on driving time towards a store for the daily goods retailer. Moreover, there is varying intra-network spatial competition depending on the type of location strategy pursued by the different retailers. Results show that for some retailers retail agglomeration effects are more outspoken than for others. However, impact of driving time on consumer intra-network store choice was independent of retail agglomeration size. Finally, results indicate that opening stores outside the pursued location strategy should be approached with care as significant impacts on sales cannibalization can emerge within the store network. These findings are important for crafting an overall expansion strategy for expansion managers as well as for marketing managers occupied with network changes at operational level.

[1]Based on: De Beule, M., Van den Poel, D., Van de Weghe, N.. Assessing the principles of spatial competition between stores within a retail network. Applied Geography 2015; 62 : 125 —135.

3.2 Introduction

Retailers in expansion are often faced with the challenge of assessing the impact of a store network extension on the performance of their existing stores within the network. To accurately understand this impact, it is advisable to look at the shopping behaviour of customers and how it is affected when faced with a modified retail landscape. Academic research already revealed a wide variety of insights in drivers of store choice and resulting theoretic choice models. However, these models and frameworks largely ignored specific spatial competitive dynamics of store within a retail network, often referred to as sales cannibalization [39]. Recently, more research has been conducted on this topic, focusing on the relevant spatial and non-spatial drivers to accurately assess shifting store choice and cannibalization of sales within a retail network [35, 102]. Knowledge around these specific drivers within a retail network can aid expansion managers with their expansion location choice, in order to avoid, for example, heavy cannibalization of sales on existing stores nearby.

This study focuses on the specific impact and spatial dynamics of driving time and retail agglomerations on intra-network consumer store choice and hence cannibalization of sales within a retail network. Knowledge about, for example, consumer tendency to prefer a multipurpose shopping trip to a large retail agglomeration over multiple single-purpose store trips to smaller retail agglomerations, is vital for a retailer to accurately assess the impact of a modified store network. If consumers will find a higher utility in combining shopping trips in one big trip to a large agglomeration, then a planned new store opening in a big, attractive retail agglomeration will have a widespread cannibalizing impact across multiple stores of the network located in smaller retail agglomerations.

Most academic studies have researched such impacts from the consumer's point of view in a well-defined regional scope or through controlled lab-experiments in order to reveal the drivers for store choice. However, assessing drivers for store choice within a retail network from a retailer's point of view requires a broader geographic scope to ensure the representativeness of the results and, desirably, a benchmark with different retailers to assess the relative impact for these drivers. This study is, to the best of our knowledge, the first that compares the spatial competitive intra-network dynamics for multiple retailers. To this end, loyalty card information and exit questionnaires are used to detect spatial patterns in consumer intra-network store choice preferences. With the use of loyalty card and exit questionnaire information, it is possible to construct store trade areas which can overlap in certain *competitive areas*. By comparing the sales distributions in these competitive areas, the spatial competitive dynamics blueprint of a retailer can be assessed. Data from six retailers selling products from three different product categories, each with their unique location strategy are examined to allow for a cross-market, cross-location strategy comparison of the spatial dynamics blueprints within their retail network. In doing so, this study aims to extend literature in two ways. First, geographic sales data of retailers offering a variety of product categories are compared for the first time in regard to their unique intra-network spatial competitive blueprint. Secondly, this study also compares the competitive trade areas of retailers offering the same category of products but following a different store location strategy. A location strategy aimed at standalone stores will arguably yield different spatial competitive dynamics between stores than a retailer aiming at opening stores in high streets. In this study, the impact of agglomerations is assessed in relation to the retailer's expansion strategy.

The remainder of this chapter is structured as follows. First, the current state-of-art in literature on assessing trade areas is reviewed and the vast research around multipurpose shopping is summarized. Next, the methodology and test design sections describe how the geographic sales data of the different retailers are used to assess the spatial competition within their store networks. The results section then unfolds the different forms of spatial competition between the studied retailers. Lastly, conclusions and managerial implications are discussed.

3.3 Literature Overview

Due to the increasing interest in objective optimization of retail network performance, research has begun to emerge around this topic. Pancras et al. [102] look into the case of a fast-food chain where they investigate the varying impact of network changes, pricing and customer satisfaction on the sales of existing restaurants. The model that was presented also included a parameter related to the distance from census tracts to the different restaurants to incorporate spatial competitive dynamics. The authors however lacked sales data at census level to verify the spatial dynamics used in the presented model.

Agglomeration effects have been the subject of much more research, albeit mostly from a consumer point of view. From this perspective, a consumer seeks to maximize its shopping utility by engaging in multipurpose shopping trips. Arentze et al. [4] investigated the influence of offer diversity in retail agglomerations to assess the increased willingness of consumers to include these stores in a one-stop multipurpose shopping trip. This research was extended by Dellaert et al. [36] and Arentze et al. [7]. Also, Brooks et al. [22] assessed the impact of varying driving times and offer configurations on store choice in a controlled lab experiment. The increased utility due to travel cost minimization by combining shop purposes in one trip has also been investigated by Dellaert et al. [37]. Rotem-Mindali [116], in turn, found that retail centers that accommodate multipurpose shopping are not necessarily located in close proximity to major residential concentrations. However, the resulting downside of longer travel times are largely compensated when having a good road-based accessibility.

A first empirical application of multipurpose shopping dynamics in the grocery market can be found in Popkowski Leszczyc et al. [107] where the authors also take the location and price strategy of the retailers into account. Next to derived consumer benefits, agglomeration effects are also induced by benefits for retailers and real estate developers. Increased competition in larger retail environments puts downward pressure on prices but this is at least partially offset by increased volumes sold [13, 21, 123]. To avoid extreme price competition however, clustering of retailers mainly occurs between retailers that can sufficiently differentiate their offering from competitors within the same retail agglomeration [104]. This is especially necessary as larger retail agglomerations tend to have higher rental prices [115], putting even more pressure on the retailer's profit margins.

Applied to a retail network, agglomeration effects have been included in various predictive analytical models. Roig-Tierno et al. [114] included a measure of passing trade in their analytical hierarchy process (AHP) for retail site location decisions. In spatial interaction models, Huff [65] developed a gravity model to predict the trade area of shopping centers. This model was later extended to accommodate for measuring agglomeration effects on store attractiveness [18, 31]. Applications of this type of spatial interaction models where agglomeration effects are explicitly accounted for can be found in Satani et al. [118], Li and Liu [90] and Orpana and Lampinen [101].

Moreover, spatial competition drivers within a retail network are known to be very important in a franchiser-franchisee case. The effects of sales cannibalization or *encroachment* of an expansion case within a franchise firm has been assessed by Kalnins [70]. Also, literature contains a fair amount of research around models to resolve these expansion conflicts. Cox and Mason [30] investigated how a model can contribute in delineating store trade areas and geographic trade rights. Also, different expansion strategies can be crafted based on what objective the franchisees seek to maximize with their retail network configuration, like minimizing sales cannibalization or maximizing total market share [32, 55, 76, 106, 128, 129]. This chapter contributes to this discussion in a way that spatial competition patterns can be assessed using known geographical sales within the network and that impact of retail agglomerations can be assessed in an objective way to include this factor correctly in a conflict resolution model and in the discussion around expansion within the franchise chain.

3.4 Methodology

This section explains how spatial competitive dynamics of intra-network store choice is assessed. Such an assessment can yield insights in how customers value drivers for store choice when choosing between different stores of the same brand to make a purchase [49]. This in turn, leads to valuable knowledge for the retailer on how stores compete for the same customers. In other words, they gain insights in the spatial intra-network competitive dynamics. Through loyalty card information, it is possible to investigate such customer behaviour as it links a geographically located customer with its behaviour towards different stores from the same brand. Moreover, loyalty card information and exit questionnaires provide such information on a large scale, which is necessary to discover valuable insights in a real life, non-controlled environment where a vast set of drivers influence intra-network store choice. Isolating the unique impact of driving time and retail agglomerations for this study thus requires eliminating many other influencing factors. These co-influencing factors can be found at both brand and store level. On brand level, time depending factors like nationally changing spending, competition and branch recognition have to be taken into account. For this study, however, geographic sales data within a timespan of one and the same year was available. This forgoes the need to implement brand level factors as all data for one retailer are consistent in time. On store level, this study aims to assess the impact of drivers as driving time and retail agglomeration synergies. This implies that all other store level drivers of store choice -like varying net sales surface, number of checkouts or availability of parking- should be abstracted as much as possible. Luckily, due to the large number of observations, it is possible to abstract these other drivers, which results in a unique assessment of the impact of driving time and retail agglomerations. To achieve these clear comparisons, a spatial assessment of sets of confluencing trade areas within a store network is conducted. More specifically, the achieved market shares on store level in census blocks where there is direct competition for its consumers between two stores from the same brand are compared to one another. This comparison is constructed as follows: As a first step, the average trade area extension of each focal retailer is examined. The focal retailer selling daily goods (see Section 3.5) has the smallest average trade area, extending on average 15 kilometers (see Table 3.1). A uniform boundary of 30 Euclidean kilometers between two stores of the same retailer is set for all focal retailers. This ensures optimal results comparability between the focal retailers while also achieving maximum probability of having confluencing trade areas between the two stores in a pair.

	Average trade area extension (kilometers)
Food retailer	15
DIY retailer	18
Fashion retailer	20
Footwear retailer	21
Fashion accessories retailer	22
Media retailer	27

Table 3.1: Average extension of each focal retailer's trade areas.

Figure 3.1 displays such competitive pairs for one of the six studied retailers.

To accurately measure direct competition between both stores within a pair, only the

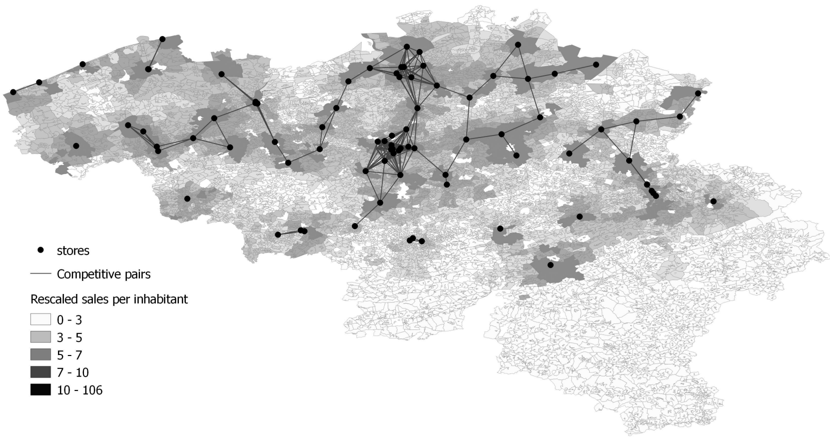

Figure 3.1: Competitive pairs of stores for an example retailer on the Belgian market.

census blocks where consumers are likely to have both stores in their choice set are withheld. To emulate this zone of direct competition, a rhombus between both stores within a pair is constructed, as shown in Figure 3.2.

Figure 3.2 shows an example rhombus with an angle α that determines the width of the zone of direct competition between both stores. For the analyses in this research an angle α of 35°was used. For this angle, the cumulative sales per square km in the average corresponding rhombus are maximal (Figure 3.3) and thus is the competition between both stores on average maximal.

Next, for these pairs, the union of census blocks that have registered sales for at least one of the two stores is withheld. These data are supplemented with corresponding driving times from the census block to both stores within the pair.

Each focal retailer has multiple pairs of competing stores, each with their own unique store related and environment related features. This makes a comparison between pairs of competing stores very difficult when the aim is only to assess the impact of retail agglomerations and driving times. To obtain the most comparable pair-based results of the direct spatial competition for customers, variations in the spatial component (varying distances between both stores and varying road network based accessibility between pairs) and the resulting monetary allocations (different competitive landscape in proximity to the pair and spatial consumer heterogeneity leading to spatially fluctuating spending potential

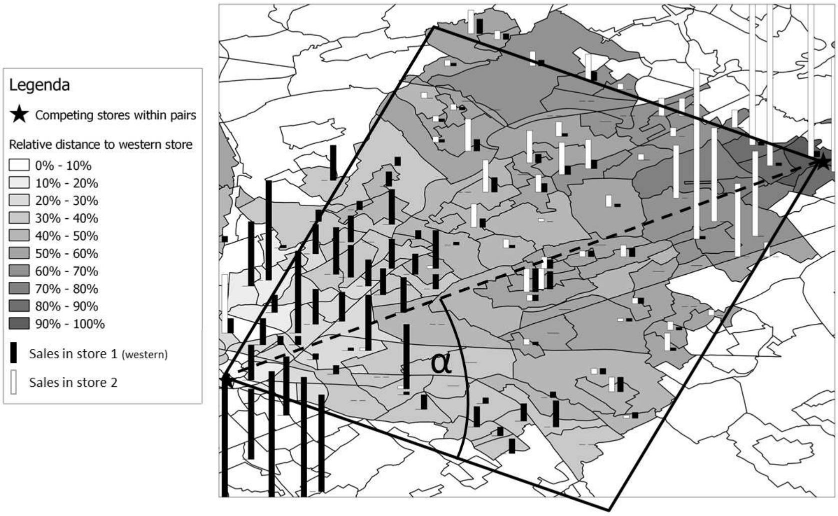

Figure 3.2: Example zone of direct competition.

in the zones of direct competition) have to be rescaled to a uniform, comparable denominator. This is achieved as follows: Take d_{j1} as the shortest-path driving time between store 1 and the centroid of census block j located within the rhombus between store 1 and 2. d_{j2} is then the shortest-path driving time between the centroid of census block j and store 2. The relative driving time to store 1 for each census block j can then be expressed as $d_{j1}/(d_{j1} + d_{j2})$ or, in other words, the relative amount of time it takes to drive from store 1 to the centroid of census block j when driving from store 1 to store 2, over census block j, holding the assumption of an undirected road network. A relative travel time of 50% then corresponds with a census block which has an equal driving time to store 1 as to store 2. For the corresponding allocations, an equal approach is applied. Take F_{j1} and F_{j2} as the monetary allocations from census block j to store 1 and store 2, respectively. The relative monetary allocation to store 1 is then $F_{j1}/(F_{j1} + F_{j2})$. Doing so eliminates influences entered by internal competition (other competing stores within the same retail network) and external competition and a varying sales potential resulting from different socio-demographic environments around pairs. By only taking pairs of stores, the influence of other stores within the same network that also compete for these geographic blocks are indeed explicitly left out. It is assumed however that these other alternatives have no influence on the *relative* preference between the two stores in the studied pair. This property is also known in literature as the independence of irrelevant alternatives (IIA-property) [109].

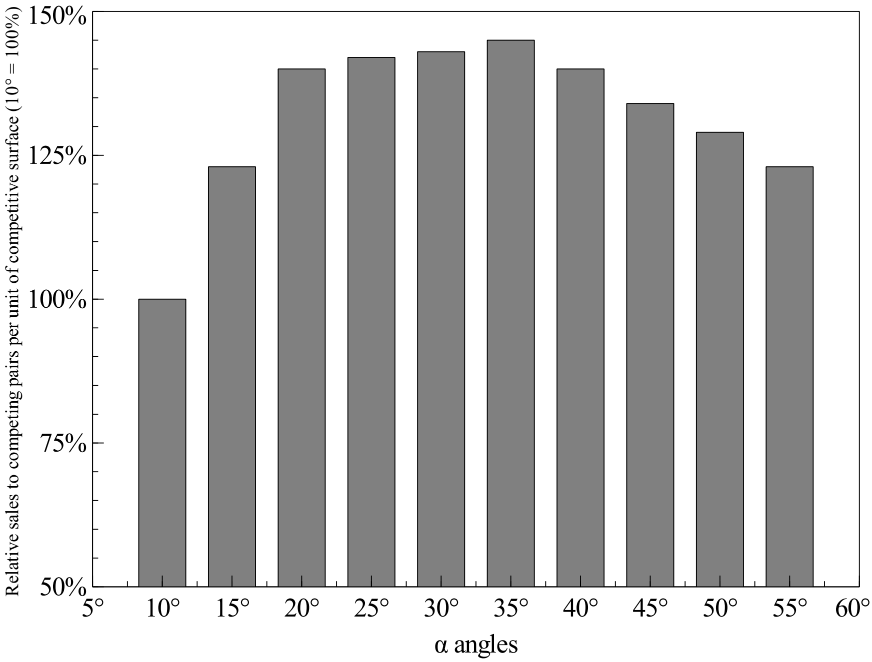

Figure 3.3: Assessment of the optimal value for angle α.

Finally, the relative allocations are averaged per relative driving time point over a whole set of pairs, each pair containing two stores with their unique store level features that drive store choice. Averaging over multiple pairs mitigates the impact of these features, unless they are explicitly taken into account when selecting pairs. Selecting certain pairs based on store features is thoroughly used in the research questions from Section 3.6. Figure 3.4 gives a graphical overview of these allocation distributions between two stores, visualizing the average relative allocation to store 1 over all pairs (y-axis) for blocks at every relative driving time point (x-axis).

It is important to note that the set of accepted pairs for the graph in Figure 3.4 also contains mirror pairs. That means that next to pair (A, B), pair (B, A) is also taken into account. When allowing this, store level drivers of store choice, except for relative driving time, are eliminated in the best way possible. Because of this property, such graphs will act as a benchmark for future comparisons. As a result, the graph for the set of accepted pairs is symmetric around the [50%,50%] point. It is indeed rational behaviour to spend an equal amount in both stores if these stores are located at an equal driving time, all other influences on store choice being equal for both stores. Figure 3.4 also shows the relative competition between two stores within a randomly chosen competitive pair for the same focal retailer.

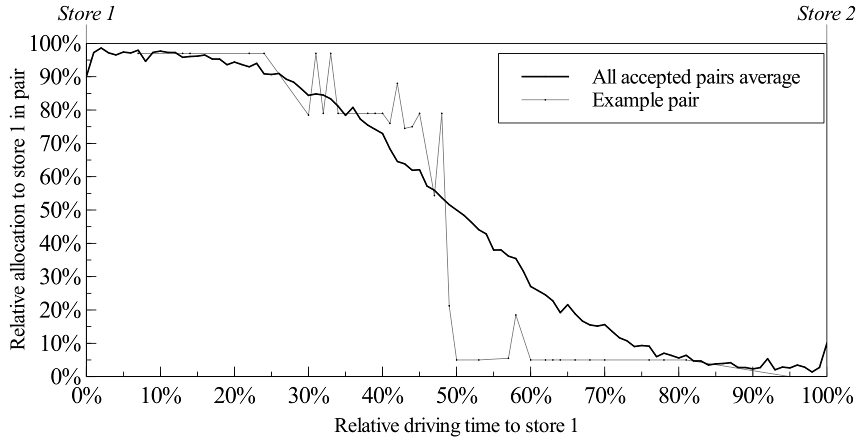

Figure 3.4: Example of relative allocations to store 1 as a function of the relative travel time (α=35°).

The relative allocation graph for the example pair shows there can indeed be significant case specific differences compared to the mirrored total average for all pairs, because all store choice influencing factors are still reflected in this graph. On the other hand, as shown before, all influences of store characteristics and retail agglomerations remain hidden in the symmetric graph, except for relative driving time.

Figure 3.5 shows the relative cumulative allocations towards stores 1 and 2 for the example pair as well as for all accepted pairs for the same retailer. At the 0% relative driving time mark, store 1's share in the total sales in the competitive area for both stores can be seen. At the 100% relative driving time mark, store 2's share in the total sales within the same scope can be verified. Since mirrored pairs are also included in the averaged pairs, relative cumulative sales to both store 1 and store 2 totals at 50%. This is not necessarily the case for an individual pair of competing stores. A shift in spatial competitiveness due to relatively better store features, like a bigger retail agglomeration, can increase the cumulative relative sales of this store above 50%, all else being equal. The stores in the example pair, however, seem to attract an equal total amount of sales from their competitive zone.

3.5 Test Design

In this study, loyalty card information and exit questionnaires for six different retailers in Belgium are used. The six focal retailers all operate in different product categories and follow different store location strategies. The product categories reflect the type of prod-

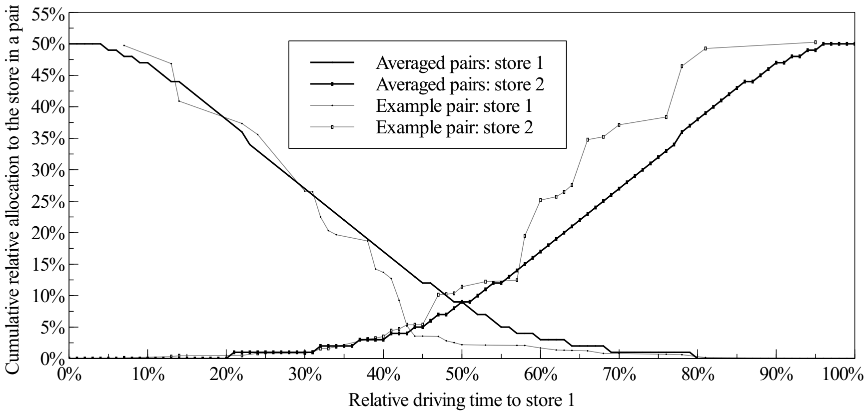

Figure 3.5: Example of relative cumulative allocations towards store 1 and 2.

uct offered by the retailer. Three main categories are usually distinguished: daily goods, exceptional goods and periodic goods, as shown in Table 3.2. Daily goods like food and personal hygiene are characterized by a high purchase frequency. Exceptional purchases, like electronics, furniture and DIY are generally known to be destination-driven purchases. Finally, periodic goods mainly feature fashion related purchases and are known to be very susceptible to be included in purpose-combining shopping trips. For the store location strategy, three retailers clearly opt for peripheral locations while one explicitly opts to be present in high streets only. The two remaining retailers follow a hybrid strategy of aiming at both high streets and peripheral locations.

	Daily	Exceptional	Periodic
Peripheral	Food retailer	DIY retailer	Fashion retailer
Peripheral and High Street	*Not many stores in general*	Media retailer	Footwear retailer
High Street			Fashion Accessories retailer

Table 3.2: distribution of focal retailers around 2 axes: product category and location strategy.

To objectively measure the extent of retail agglomeration, the Belgian shopping areas are categorized based on their size (see Table 3.3). The cutoff rules are set arbitrarily while a minimum number of shopping areas within each category is ensured. The top 35 shopping areas in Belgium are characterized by having at least 70 stores at walking distance from one another and are classified as major retail agglomerations. All major high streets in Belgium are included in this category. Medium shopping areas on the other hand contain between 30 and 70 stores at walking distance from one another and can be seen as locally well-known shopping areas. Shop areas with less than 30 stores at walking distance from one another are labeled as small and are spread numerously throughout the country.

agglomeration type	Number of stores at walking distance
Small retail agglomeration	less than 30
Medium retail agglomeration	between 30 and 70
Large retail agglomeration	more than 70

Table 3.3: The classification of different retail agglomeration sizes.

The first retailer is a supermarket chain with 79 stores in Belgium (see Table 3.4). It opts to be present in smaller retail agglomerations in order to be generally well accessible to its customers. The second retailer is a major DIY retailer with 84 stores in Belgium. While it primarily aims to be located in smaller retail agglomerations, it also has some stores in medium retail agglomerations. The third retailer sells middle segment fashion with 70 stores across Belgium. Unlike most fashion retailers, its location strategy aims at major traffic axes towards cities rather than city centers, which is reflected in their main presence in smaller retail agglomerations. Two retailers follow a hybrid location strategy: a multimedia and book retailer with 132 stores in Belgium is both active in big city high streets and in minor cities or larger villages. The second retailer is active in the middle segment footwear market with 69 stores. Lastly, the fashion accessories retailer has 100 stores across Belgium and focuses primarily on big city high streets, which is reflected in its presence in all large retail agglomerations in Belgium with at least one store. Due to their presence in all large retail agglomerations, they also have a major share of their stores in medium sized retail agglomerations.

	Nr of stores	Stores per agglomeration classification		
		small	medium	large
Food Retailer	79	79 *(100%)*	0	0
DIY Retailer	84	71 *(85%)*	13 *(15%)*	0
Fashion Retailer	70	60 *(86%)*	9 *(13%)*	1 *(1%)*
Footwear Retailer	69	39 *(56%)*	13 *(19%)*	17 *(25%)*
Media Retailer	132	71 *(54%)*	34 *(26%)*	27 *(20%)*
Fashion Accessories Retailer	100	7 *(7%)*	55 *(55%)*	38 *(38%)*

Table 3.4: Overview of store distribution among the focal retailers.

For the comparison of the spatial competition dynamics between pairs of stores, loyalty card information and exit questionnaires are examined. For privacy reasons, the geocoded customer location from the loyalty card is abstracted to the zone the provided address is located in. Exit questionnaires consist of a simple inquiry at the checkout for the customer's postal code. The provided geographic information was formatted as annual figures, from 2010 data for the food retailer to 2013 data for the footwear retailer. Data from each retailer is however consistent in time, with all data for each retailer covering the same entire year. The geographic allocations resulting from the loyalty cards and exit questionnaires were proportionally adjusted to match the annual store sales. The driving times in turn were calculated using OpenStreetMap data and a shortest-path routing algorithm, PgRouting.

Retail agglomeration data were acquired from Locatus, an on-the-field data supplier with a market-leading database of more than 200.000 retail and service stores in Belgium. They also provide a classification of the retail agglomeration every store belongs to, based on the rule of thumb that all stores within the agglomeration are at walking distance from one another.

Figure 3.6 depicts the different research questions that will be investigated. The first comparison that can be made covers the specific spatial competitive patterns for customers along the product category axis. This research question mainly concerns the impact of relative driving time on intra-network store choice for consumers. In the second research question the focus shifts towards the impact of retail agglomerations on store choice. For this research question, the retailers with a hybrid location strategy are in scope. The third and final research question, on the other hand, investigates the other retailers with a clear location preference focusing on either peripheral or high street locations. They do however sometimes expand to locations outside their core store location strategy. This research question then investigates the impact of the differentiating retail agglomeration sizes on the intra-network store preference for their customers.

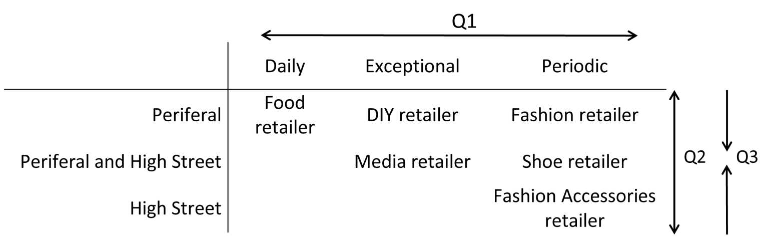

Figure 3.6: Visual representation of the research questions.

3.6 Results

In this section the results for the pairwise comparison of intra-network store choice along the two axes of the matrix (Figure 3.6) are presented, and answers to the relative impact of driving time and retail agglomerations on consumer intra-network store choice are provided through the three research questions.

Q1: The impact of driving times on intra-network store choice along the product category axis

The first comparison that can be made is to compare the spatial competition between pairs of stores for retailers that offer products from different categories: daily, periodic and exceptional goods. Table 3.5 shows the number of accepted competitive pairs for each retailer for this research question. As the research focus is on the impact of relative driving time, other influences -like brand, store and environment related influences- should be abstracted from the results as much as possible. This implies the inclusion of all pairs, including mirror pairs.

	Nr of accepted pairs
Food retailer	1094
DIY retailer	360
Fashion retailer	186
Footwear retailer	320
Media retailer	1328
Fashion accessories retailer	466

Table 3.5: Number of accepted competitive store pairs for Q1.

Figure 3.7 then shows the relative sales distribution to store 1 for every pair of stores for the three retailers with a peripheral location strategy. As mirror pairs are also included, Figure 3.7 is symmetric along the 50% points of relative driving time and relative allocations. All retailers but the food retailer follow a similar curve for the relative allocation of sales, while the food retailer has a more expressed sigmoid function, with a steeper descent along blocks at almost equal driving time to both stores. The impact of driving on intra-network store choice is clearly a lot more significant for the food retailer. As the frequency of purchasing at stores selling daily goods is much higher than for stores selling products from other categories, the impact of driving time on intra-network store choice logically carries more weight. Furthermore, as the focal food retailer has only stores in small retail agglomerations, a possible attenuating effect of purpose-combing shop tripping on the impact of driving time is virtually non-existing for this retailer. These findings are also in line with findings by Rhee and Bell [113], who discovered that 94% of all grocery purchases are effectuated in the same grocery store. They find that, among others, a convenient location is vital for consumers when choosing their most-preferred grocery store. A similar clear preference pattern for one particular grocery store can also be seen in Figure 3.7. Ellickson and Grieco [41] found that a Wal-Mart entry in a local US grocery market has an observable spatial effect on competitors up to just 2 miles, again confirming that proximity to the customer is an important driver for store choice specifically in the grocery market.

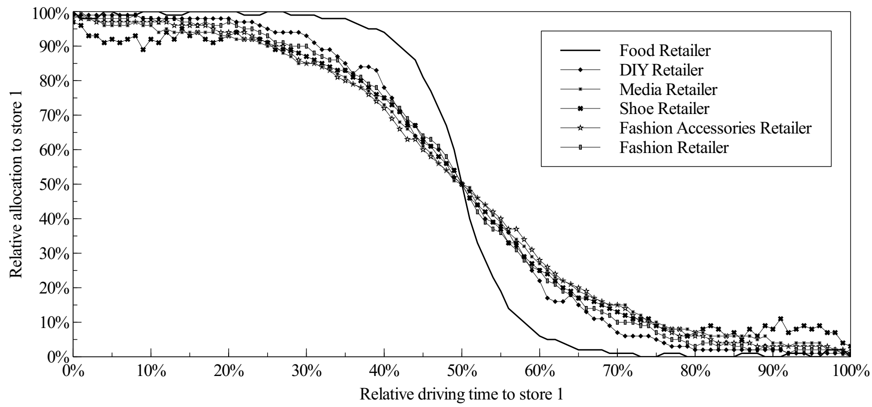

Figure 3.7: Cross-product category pairwise comparison of relative sales for all focal retailers.

Q2: Spatial competition for retailers with hybrid location strategies

Retail agglomerations can induce multipurpose shop tripping and thus alter store choice. Including an otherwise lower utility yielding store - due to longer driving time - can now yield a higher utility when its visit is combined with visiting other stores in the same retail agglomeration. This means that retailers that opt to be present in both small and large retail agglomerations can witness different forms of spatial competition for customers between stores, depending on the size of retail agglomerations the stores are located in. In the first part of the second research question, Q2a, the spatial competition for customers between a store located in a larger retail agglomeration and a store in a small retail agglomeration is investigated. There might also exist a different pattern of spatial competition between stores that are located within approximately the same size of retail agglomerations. The impact on spatial competition for pairs of stores in these cases is investigated in the second part of this research question, Q2b.

Q2a: The impact of retail agglomerations on spatial competition

The focal retailers following a hybrid location strategy, in this case the media and the footwear retailer, have both a fair share of their stores located in small and large retail agglomerations. This means that their brand strength and the kind of products sold enables them to be successfully active in both types of agglomerations. For example, the media retailer is a well-known brand that also sells newspapers and magazines, which generates enough daily traffic in smaller retail agglomerations to be viable. Spatial competition, however, can be quite disturbing for those stores in small agglomerations having a competing store from the same brand in a large retail agglomeration nearby. The increased utility for a customer due to multipurpose shopping possibilities in larger shopping agglomerations leads indeed to an increased willingness to travel further to these larger agglomerations, resulting in a larger trade areas. These larger trade areas in turn have an increased possibility of confluencing with trade areas of other stores within the network, thus resulting in increased spatial competition for the same customers. This possible issue is investigated in this section.

Table 3.6 shows the number of pairs of stores for both retailers that witness direct spatial competition for customers where store 1 is located in a major retail agglomeration and store 2 is located in a minor retail agglomeration. These results are compared to the symmetric benchmark situation where also mirror pairs are included, resulting in the abstraction of the impact of retail agglomerations on store choice within pairs (see Figure 3.8).

	Nr of accepted pairs
Footwear retailer	59
Media retailer	168

Table 3.6: Nr of pairs in direct competition with store 1 located in a large retail agglomeration and store 2 in a small retail agglomeration.

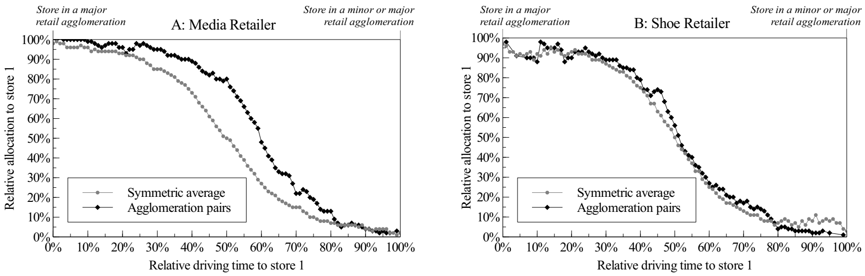

Figure 3.8: Different spatial competition patterns with varying retail agglomeration magnitudes for the media and footwear retailer.

The results from Figure 3.8 imply that for the media retailer, relative sales and thus store choice in the region of direct competition is much more shifted towards the store in a major agglomeration than in a similar case for the footwear retailer. This could indicate that buying shoes in stores of the footwear retailer is much less likely to be included in a one-stop, multi-purpose shopping trip. However, a more likely explanation is that the footwear retailer, due to a strong brand name, benefits marginally less from retail agglomerations, because their customers are attracted to the brand rather than to the retail agglomeration. The Media retailer on the other hand should be more wary about the effects of opening a store in a major retail agglomeration on the sales of existing outlets in smaller retail agglomerations located in the vicinity.

Figure 3.9 shows the average cumulative relative sales to both stores in the accepted pairs for both retailers. For the media retailer, a store in the large retail agglomeration captures on average 60% of the total sales to both stores in the zone of direct competition. The store in the smaller retail agglomeration thus captures on average 40% of the total sales to both stores in the same area. The benchmark graph, on the other hand, including all pairs and mirror pairs, results in a logical fifty-fifty split. The major shift in store preference towards a store in a larger retail agglomeration can be seen for consumers that are located closer to the smaller retail agglomeration (i.e. past the 50% relative driving time mark). In this area, there is a clear difference in steepness of the curves for the benchmark and the agglomeration pairs. For the footwear retailer, the difference between both curves is minimal, which corresponds to the results in panel B from Figure 3.8.

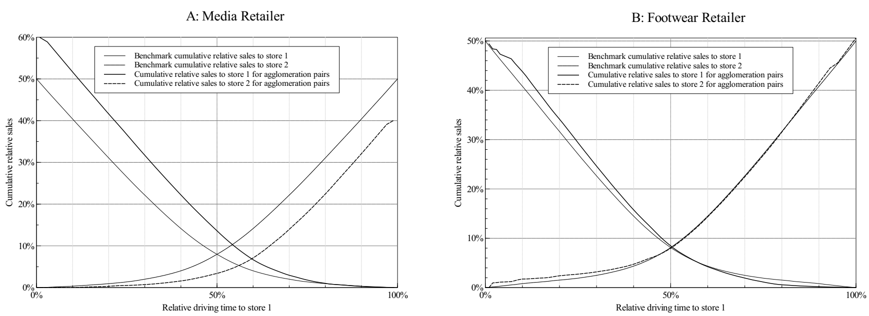

Figure 3.9: Average cumulative relative sales to both stores 1 and 2 within the accepted pairs for varying retail agglomeration sizes for the media and footwear retailer.

Q2b: Spatial competition between stores in similar retail agglomeration sizes

While Q2a answered the question on how spatial competition manifested itself for stores in varying retail agglomeration sizes, spatial competition for customers can also differ between pairs of stores located both in about the same size of retail agglomeration, and which thus yield equal utility from purpose-combining shop tripping. To assess this, the sales data of the retailers with a hybrid location strategy are used, as they possess the most equal spread of stores across retail agglomeration sizes. Table 3.7 shows the number of pairs that satisfy the condition for this part of the research question.

Figure 3.10 shows that there is no different spatial competition pattern for pairs of stores who are located in retail agglomerations of about the same size. This implies that the impact of driving time on store choice does not change if two stores in about the same retail

	Nr of accepted pairs		
	small	medium	large
Footwear retailer	98	12	18
Media retailer	336	98	54

Table 3.7: Number of accepted pairs for both retailers following a hybrid location strategy.

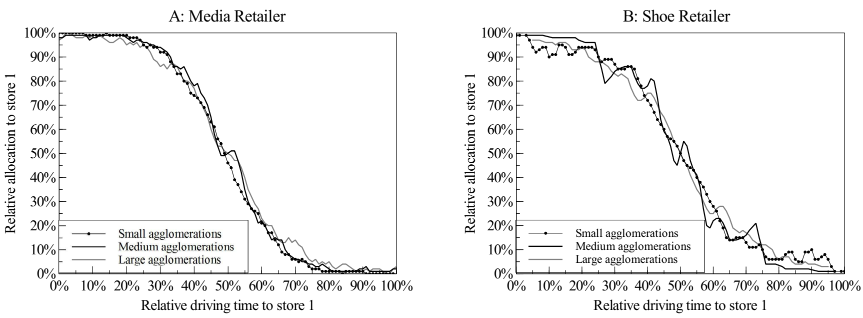

Figure 3.10: Spatial competition for pairs within the same retail agglomeration size for the media and footwear retailer.

agglomeration size are in a customer's choice set, which can be explained by the equal derived utility of the retail agglomerations for both stores.

Q3: Effects on spatial competition outside the retailer's core location strategy

Each retailer has chosen its location strategy very careful as a function of their product offering, brand strength and overall strategy. However, large retail agglomerations are scarce and it is not likely many more will be allowed to be constructed in an already saturated retail market. For further growth, it is then necessary for retailers strategically focusing on these large retail agglomerations for expansion to move down to smaller retail agglomerations. On the other hand, retailers focusing on peripheral, smaller retail agglomerations have a more abundant choice set for expansion. However, they sometimes get an opportunity to test their concept within larger retail agglomerations. In these cases it is then interesting to see how their store concepts work outside their core location strategy. In Table 3.4 we can see that the DIY and Fashion retailer already have some stores outside their core location strategy of opening peripheral stores. Comparing the spatial competition between stores located outside and inside their core focus of small retail agglomerations allows to assess what the cannibalization effects of moving outside the core location strategy are. Table 3.4 also shows the Fashion accessories retailer has opened stores in medium and smaller retail agglomerations while its core location strategy is to open stores in major retail agglomerations. By assessing the spatial competition between stores in major agglomerations versus those in smaller agglomerations, it is possible to determine the cannibalization risks of further expansion towards smaller retail agglomerations.

	Agglomeration size		
	Store 1	Store 2	Nr of accepted pairs
DIY retailer	> 30	≤ 30	54
Fashion retailer	> 30	≤ 30	23

Table 3.8: Number of accepted pairs for Q3 for the DIY and fashion retailer.

Table 3.8 shows the number of accepted pairs based on which can be investigated how the DIY retailer and fashion retailer benefit from being located in increasing sizes of retail agglomerations.

Figure 3.11 shows how spatial competition patterns between stores can differ when one store (store 2) is located in a retail agglomeration outside the general store location strategy of the retailer, while store 1 is located within the core location strategy. The benchmark graph shows the spatial competition patterns when both stores of a pair are located within the core location strategy. Part A clearly indicates that for the DIY retailer, very few agglomeration effects can be noted when a store (store 2) is opened in a medium agglomeration. For this retailer, this is an important conclusion, for commercial real estate rental prices are often higher in larger retail agglomerations [115], while there is no clear evidence the store also benefits from synergy effects with other retailers in these agglomerations. In part B of Figure 3.11 some small differences in spatial competition can be noted for the fashion retailer in favour of the store located in the larger retail agglomeration. This might give an indication for the retailer to further investigate the viability of opening stores in larger retail agglomerations.

Figure 3.12 shows the average cumulative relative sales to both stores in the accepted pairs. Panel A shows there is no clear difference between the pairs of DIY-stores that are both located within the core strategy of peripheral locations and pairs of stores with one store (store 2) located outside and one (store 1) located within the location strategy. In both cases, on average 50% of the total sales to both stores in the area of direct competition goes to either store. Panel B on the other hand shows that for the fashion retailer, there is a minor shift in preference and thus in total accumulated sales towards store 1, located in a larger retail agglomeration. On average up to 5% of the total sales to both stores within a pair shifts to the store in the larger retail agglomeration. Comparable to panel A of Figure 3.9, the increase in curve steepness and thus shift in store preference can mainly be seen for customers past the 50% relative driving time mark, i.e. for customers located closer to the store in the small retail agglomeration (store 2). They will derive more utility from combining shopping purposes in the larger retail agglomeration which offsets the additional

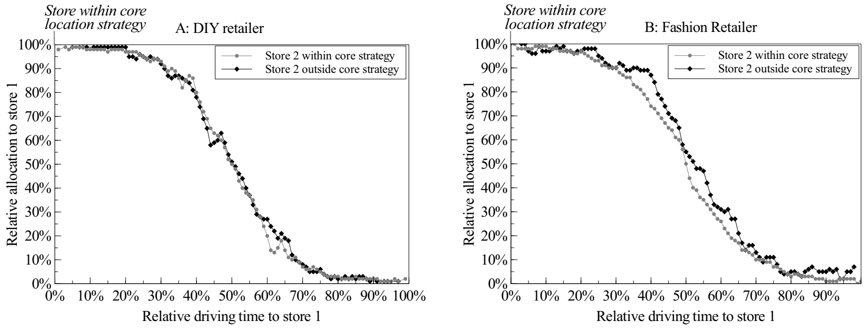

Figure 3.11: Comparison of spatial competition patterns within and outside the general location strategy for the DIY and Fashion retailer.

time cost compared to a visit to the store in a smaller retail agglomeration.

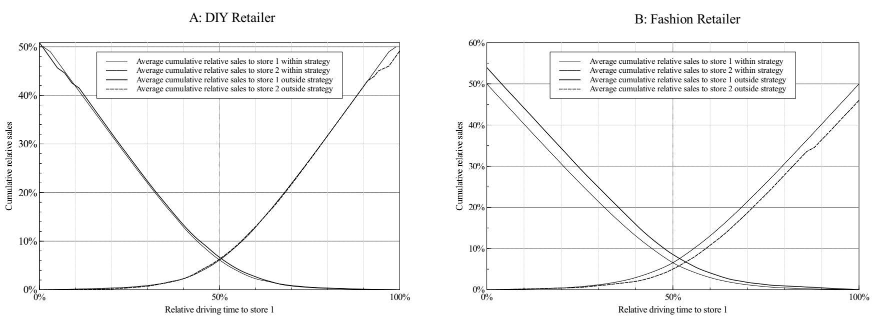

Figure 3.12: Comparison of the average cumulative relative sales for pairs with store 2 within or outside the general location strategy for the DIY and Fashion retailer.

To facilitate further growth and expansion, the fashion accessories retailer has to expand towards smaller retail agglomerations as it is already present in all major retail agglomerations in Belgium. However, spatial competition for customers located between a store in a smaller retail agglomeration and a store in a larger retail agglomeration might be settled in favour of the store in the larger retail agglomeration if purchasing in a store of this brand is largely susceptible to be included in one-stop multipurpose shopping trips. In this case the viability of opening a store in a smaller retail agglomeration could become questionable. Table 3.9 shows that the retailer has already expanded towards smaller retail agglomerations.

	Agglomeration size		
	Store 1	Store 2	Nr of accepted pairs
Fashion accessories retailer	≥ 70	< 70	116

Table 3.9: Number of accepted pairs for Q3 for the DIY and fashion accessories retailer.

Figure 3.13 shows the spatial competition pattern for pairs of stores for the fashion accessories retailer. Pairs of stores where both stores are located in major agglomerations are compared to pairs of stores where store 1 is situated in a major retail agglomeration and store 2 is situated in a small or medium retail agglomeration. The figure clearly shows that stores in smaller retail agglomerations that are in direct competition with larger neighbours suffer from the customer's preference for a one-stop, multi-purpose shopping trip to the larger retail agglomeration. The retailer, planning a new opening in a smaller agglomeration in the vicinity of a large retail agglomeration where he is already present, should thus be very wary of the vast existing influence from the large retail agglomeration.

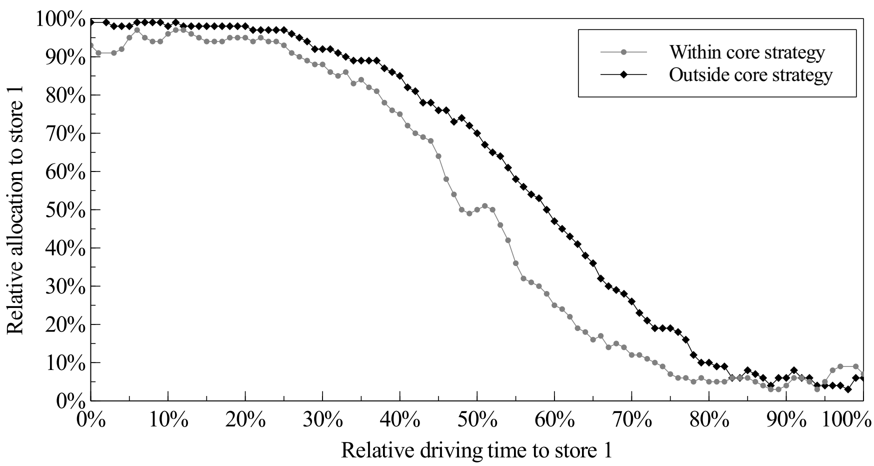

Figure 3.13: Comparison of the spatial competition between pairs of stores within and outside the general location strategy of the Fashion accessories retailer.

Figure 3.14 indicates that if there is direct spatial competition for customers between a store in a smaller retail agglomeration and an existing store in the network located in a larger retail agglomeration, on average up to 8% of sales to both stores in the zone of direct competition will shift towards the store in a major retail agglomeration due to increased utility for customers in combining shopping purposes in the large retail agglomeration. Comparable to panel A of Figure 3.9 or inversely to panel B of Figure 3.12 , the major shift of store preference compared to the situation where store 2 is also in a major retail agglomeration, can be found for customers located closer to store 2.

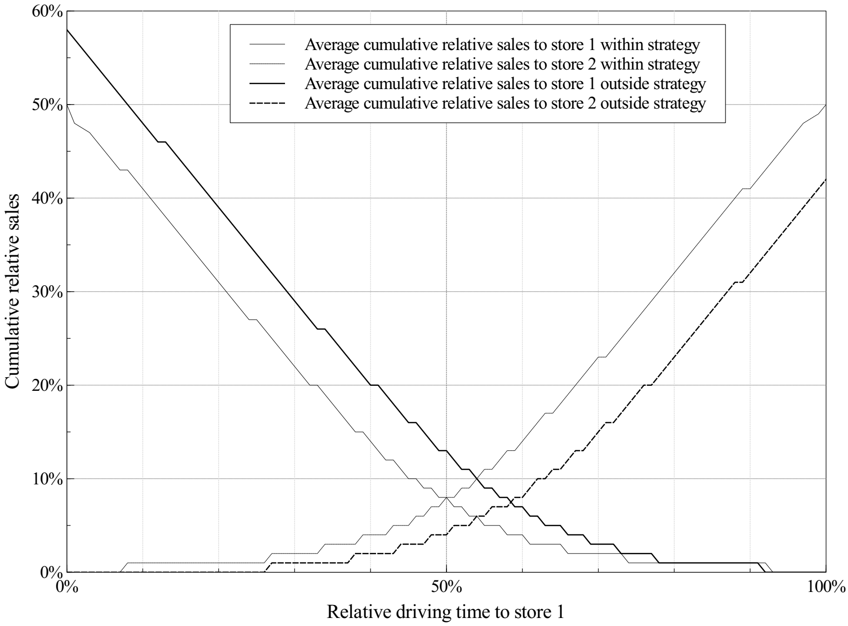

Figure 3.14: Comparison of the average cumulative relative sales for pairs with store 2 within and outside the general location strategy of the fashion accessories retailer.

3.7 Discussion and Conclusions

From the above presentation of results, it is clear that the spatial dynamics of internal competition for customers is different for varying product categories and store location strategies. Consumers are much more driving time sensitive for the super market retailer in the daily goods category than for the other studied retailers in periodic or exceptional goods. Furthermore, this research has also shown that there is a different impact of unequal retail agglomeration size for competing stores of different retailers. However, there was no clear evidence that driving time had a varying impact for competing stores in retail agglomerations of about the same size. Finally, there was also a varying impact of retail agglomeration size on spatial competition for customers between two stores when retailers move outside their core location strategy.

These conclusions have a significant managerial impact for both expansion strategies as well as marketing strategies. In expansion strategy, it is vital that the retailer's specific spatial competitive blueprint is taken into account, with specific attention to the varying impact of driving time and a varying impact of retail agglomeration sizes. For the daily goods retailer, the expansion strategy should for example be focused on a geographic spread of stores to avoid high cannibalization of sales of existing stores, which is clearly driven by driving time. In this case delineating future trade areas could be based on closest proximity to the customer. While other retailers, mainly strategically focusing on high streets and with a similar spatial competitive blueprint as the fashion accessories retailer in our study, should be very cautious about expanding to smaller retail agglomerations and maintain a focus on purpose-combining shoppers in larger retail agglomerations. For them, an expansion strategy focusing on geographic spread is inferior as derived utility and thus willingness to travel further to a larger retail agglomeration will clearly be much higher. Expansion to larger consumer attraction poles is then advisable as cannibalization of sales within the network will then be minimized.

Moreover, geographic marketing strategies such as leaflet distribution can be optimized using findings of this research. For the grocery retailer, geographically separated store-tailored folders are advisable as there is a clear division line between trade areas based on driving time. For the other retailers, this division line is much less present, and it can be advisable to cluster folders in areas where pairs of stores are competing directly for the same customers. Furthermore, the cost of a joined folder can also be divided according to their relative share of sales in these areas of direct competition. Also, for any franchise chain, investigating the spatial competition between stores is of major importance. In such an environment, much discussion around expansion involves concerns of incumbent franchisees on the cannibalization of their sales by a possible network extension. Using the findings of this research, a well-founded answer can be given to this concern and tailored steering actions can be undertaken to mitigate the negative effects for the incumbent franchisees.

Moreover, it is a common phenomenon in franchise chains to operate within judicially defined geographic zones. With the findings of this research, these zones either can be delineated objectively if there is clear geographic competition based on driving time, or can be reevaluated and their added value questioned if existing judicial zones already exist and there is no clearly separated geographic competition, as was the case for most retailers.

Lastly, during the development of new retail agglomerations, it is vital to predict its impact on local consumer behaviour in order to assess the continued viability of neighbouring retail agglomerations [68, 132]. In this light, this study allows for a detailed, store-based assessment of the cannibalizing effects on neighbouring retail agglomerations, especially when retailers are already involved in the planning stage of such new retail agglomerations.

This study is however limited to the assessment that driving times and retail agglomerations can have a varying impact for different retailers. Therefore, future research could shed some light on the influence of other store and environment related drivers for store choice. Next to that, it cannot give an indication on how much sales will be cannibalized on existing stores in case of a network expansion. To this end, a model like presented in Pancras et al. [102] can be used, with the findings of this research as relevant input parameters. Any predictive model taking the spatial component into account should thus take its own specific intra-network spatial competition parameters into account in the right way. In doing so, these models are able to accurately assess the net impact of a modified store network on geographic block, store and network level. Future research should indicate how these dynamics may be taken into account in such a model. Also, the pairwise comparison strategy followed in this chapter can also be extended in case the sales data of (some) competitors are known. In this way, the competitive strength, expressed in a geographical competitive blueprint, can be assessed and taken into account for future expansion and market share capturing strategies. Furthermore, the definition of retail agglomeration environments could be specified on a more fine-grained level. Rather than taking the total set of neighbouring retail outlets, it is possible to detect retailer-specific clustering and avoidance patterns with certain types of retail categories [24, 64, 80] and linked retail agglomerations [116]. Clustering with complementary retailers while avoiding neighbouring non-complementary retailers leads to even higher utility for consumers, reinforcing attraction of the store and thereby increasing intra-network sales cannibalization in its trade area.

4

What drives shopping area performance? An assessment of different area typologies in Flanders using open survey data[1]

4.1 Abstract

Spatial clusters of stores, also known as shopping areas, exist in different formats, most commonly city centers, shopping malls and out-of-town shopping strips. In this study, stated shopping area choice for periodic goods and perceptions of qualitative area attributes from $16,000$ phone surveys, for which the results are publicly available, are complemented with quantitative spatial configuration metrics of the shopping areas under study. The attributes are used to explain the varying sales performance for periodic goods of the different area formats in Flanders, Belgium. The perceived shopping atmosphere, the presence of adequate gastronomic facilities and the dense clustering of stores vary significantly across formats and contribute in general positively to the superior performance of shopping malls and city centers over peripheral shopping strips. This is further enhanced with a usually larger size and better relative proximity of city centers and shopping malls within the spatial choice set of consumers over shopping strips. A better local accessibility by car was

[1]Based on: De Beule M., Van den Poel D. & Van de Weghe N.. *What drives shopping area performance? An assessment of different area typologies in Flanders using open survey data*. Unpublished manuscript.

found to be significant for improved success within the set of shopping strips, but not within the set of city centers. Accessibility by public transportation was not found to be significant for either format. The results confirm or extend the current knowledge on leverages for shopping area success that can be useful for urban planners and retail policy makers as well as shopping area developers or managers.

4.2 Introduction

In the retailing landscape in many countries, a significant amount of shopping areas continue to be developed [82, 86, 130]. These developments mainly consist of newly conceived out-of-town shopping malls or organically growing shopping strips along major traffic axes outside the city center. This leads to an increasingly fierce competition with the classic shopping areas in city centers. The resulting retail facility vacancies that can be found in city centers pose a challenge for urban planners and policy makers. They see retail as an integral part of the urban tissue as it creates positive externalities to society from a social, mobility and environmental point-of-view [86]. A better quantification and objectification of underlying attributes of attractivity or performance of the different shopping area formats is therefore important. It can give urban planners and policy makers the necessary tools and leverages to counter the out-of-town development stream and revitalize retail in city centers. Next, retailers can benefit from these insights to better forecast their individual commercial success in a specific retail area (format). Finally, insights in the varying impact of manageable attributes are also useful for retail real estate developers and managers that seek to maximize shopper attraction to guarantee maximum occupancy rates and commercial success of the individual stores in their retail area.

Ample shopping area research has been published on the way endogenous and exogenous shopping area attributes impact attractivity or shopper satisfaction. Nonetheless, Teller and Elms [130] pointed out that most research has been focused on a single shopping area format. Moreover, if research is to be conducted across multiple formats, the required data for such research scales accordingly. Dolega et al. [38] and Lambiri et al. [86] argued that such large-scale data are often not available. As a result, we only found limited research on larger scales (e.g. more than 10 shopping areas). Finally, research that links to actual shopping area performance, rather than attractivity or satisfaction, is much more limited [3, 88, 94]. In light of the aforementioned challenges for urban planners, retailers and real estate developers, it is crucial to link attributes to economic performance, as it is the latter that ultimately convinces retailers and real estate developers in location decisions.

This study tries to overcome these gaps by using the publicly available results from a telephone survey of $16,000$ households in Flanders, Belgium. This inquiry surveyed the specific shopping area choice for periodic goods (e.g. clothing or shoes). It also surveyed the respondent's qualitative perceptions of various shopping area attributes. We extrapolate the stated shopping area choices to the entire population of Flanders to construct a measure for sales performance of each major shopping area in Flanders. We also complement the qualitative attribute perceptions with quantitative metrics from spatial modeling on the endogenous and exogenous configuration of each area.

This chapter is structured as follows: Section 4.3 gives an overview on different shopping area attributes that have been noted in existing literature to impact attractiveness, performance or visitor satisfaction for shopping areas. Section 4.4 explains the scope of the survey, the spatial configuration metrics and the measure of shopping area performance that are used. Section 4.5 explains the relationships found between the different attributes and shopping area performance. Section 4.6 outlines the impact of the findings for different retail stakeholders and discusses the limitations to this research.

4.3 Literature Overview

Teller and Reutterer [131] classified various choice-influencing attributes of shopping areas into 4 categories: (1) Site-related factors, (2) tenant-related factors, (3) environment-related factors and (4) buying situation-related factors. The latter category refers to the personal background to which consumers choose to visit a shopping area. This could be related to certain sociodemographic features and specific shopping tasks [134] or purposes [5, 7]. Because personal motivations are situation-dependent and have not been surveyed, this category is outside the scope of this study. We will use the remaining categories to give an overview on existing research findings and point out to what degree we have incorporated these attributes in this study.

Site-related factors

Spatial interaction between consumers and a shopping area can only exist when a consumer travel towards the area, buys and returns [65]. This physical separation that needs to be overcome, commonly expressed as an incurred time cost, is therefore a determinant for shopping location choice. Dellaert et al. [37] found that the total travel time is one of the most frequently present attributes in the mental representations of a shopping trip when a consumer decides where to shop. Various other studies confirmed travel distance as a prime evaluation criterion for shopping location choice [60, 62, 111]. The total travel time depends not only on the spatial separation from the consumer's origin, but also on the structural obstacles that need to be overcome like traffic jams or road works [130]. Moreover, the degree of micro-accessibility around a shopping area is another attribute related to total travel cost. For shoppers that visit by car, micro-accessibility mainly relates to *the last mile* (ease of finding a parking facility), the size of local parking facilities and parking fees near the shopping area. Studies between 1990 and 2000 generally showed a positive relationship between ample, nearby and/or free parking facilities and shopping area attractiveness [10, 133]. In a later study, Teller and Elms [130] found no such positive relationship towards attractiveness when interviewing consumers during a shopping area visit (i.e. *in vivo* questionnaires). But, when interviewing consumers at home (*in vitro* questionnaires), they did find a positive relationship. By contrast, Mingardo and van Meerkerk [94] found no clear relationship between the supply of parking facilities and store turnover in shopping areas in a 2012 study in the Netherlands. For shoppers that travel with public transportation, micro-accessibility refers to the proximity of stops and the frequency and variety of connections. In this research, spatial accessibility of shopping areas is taken into account by calculating road-based travel times between spatially distributed consumers and shopping areas and incorporating these costs in a gravity-model based approach. Micro-accessibility of shopping areas by car and public transportation has been surveyed during the enquiry (see section 4.4). Hence, it enables us to estimate if and to what degree the different aspects of spatial accessibility contribute to the performance of different shopping area formats.

Tenant-related factors

Shoppers also weigh the number of stores in each shopping area alternative when making shopping location decisions [37]. These agglomeration effects refer to density economies when multiple retailers are located close to one another, creating more possibilities of combining shopping of different goods in one location [4, 5, 7, 132]. Dellaert et al. [36] and Brooks et al. [22] showed that consumers like to combine purchases to minimize the chances of a no-purchase shopping trip. Teller and Elms [130] and Drezner and Drezner [40] argued that a larger variety of tenants was one of the most influential attributes of a shopping area to respectively its attractiveness and its image. LeHew and Fairhurst [88] found that larger shopping malls in terms of sales space were more likely to be ranked among the better performing ones. Moreover, with combining multiple (shopping) purposes in one location, a reduced impact of travel time is found because a larger travel cost is offset by higher combined shopping utility in a larger agglomeration [131]. This relationship between site- and tenant-related factors implies that a larger agglomeration usually has a larger area of customer attraction [38, 49, 77]. This larger market size effect offsets fiercer price competition between growing numbers of densely located tenants. In addition, shopping-driven market segments, like clothing, exhibit high product variety, mitigating further the need for fierce price competition. Next to size, the perceived quality of retail offering is also considered by consumers. The quality of offering refers to the uniqueness of the offering as well as the presence of well-known branded anchor stores [46]. Literature has not found a unanimously positive effect of these anchor stores (for example, Finn and Louviere [46] found a positive effect, while LeHew and Fairhurst [88] did not). Moreover, as shopping exhibits a social component [8], non-retail tenants (like cafes, restaurants or entertainment venues) can enhance the pleasantness and image of a shopping area [2, 100, 122]. By contrast, research by Teller and Elms [130] found no impact of available gastronomy or entertainment facilities on any dimension of attractiveness of shopping areas. Finally, other tenant-related factors such as friendliness of personnel [60] and price/value-perception [130] or vacancies [38] have been detected as contributors to shopping area attractiveness, though only to a minor degree. In this research, the aforementioned gravity-model based approach of evaluating the spatial interaction between consumer and shopping area is complemented with information on agglomeration size as both factors cannot be looked upon separately.

The perceived quality of offering and the gastronomy facilities have been surveyed during the enquiry unlike friendliness of personnel and price/value-perceptions. Vacancies are not taken into account as it can be endogenous to shopping area performance. Hence we are bounded to the former two qualitative attributes in this study (see section 4.4).

Environment-related factors

Consumer attraction towards shopping areas also stems from non-commercial attributes that improve the visitor's experience. The ease of orientation and walking routes within the area reduce for example the *in vivo* travel cost and the risk of no-purchases [3, 37]. Teller and Elms [130] limited this finding to the format of shopping malls only in their study on shopping area attraction. As a next attribute, the perceived shopping atmosphere also contributes to its enjoyment [136], image [122] and overall attractiveness [130]. Atmosphere has been found to refer to aesthetic appeal [40, 136], levels of maintenance [33, 100], odor [33, 93] and security [40]. In this research, the ease of orientation and walking routes is proxied by a co-location concentration metric borrowed from geographic literature that uses specific in-area tenant location information. The perceived atmosphere in a shopping area was part of the survey. As environment-related factors are manageable influencers of shopping location choice once a shopping area is in operation, we particularly aim to yield insights in the varying impact of these features on the performance within different shopping area formats.

4.4 Data and Methodology

Survey and shopping area data

This study builds on $16,000$ home-based telephone surveys on actual shopping area choice in Flanders and a multi-attribute qualitative evaluation of these shopping locations. The surveys were ordered by the five Flemish provinces in 2013, and were collected between March 2013 and October 2013. To ensure optimal spatial sample spread, at least 30 respondents from each municipality were surveyed with a random sampling strategy (Flanders is divided in 308 municipalities). In municipalities with a relatively high population, more respondents were surveyed. Respondents were asked to quote their top two shopping areas in terms of expenditure on periodic goods, like clothing or shoes, with the approximate guideline that in the primary shopping area they did about 75% or more of their shopping expenditures on periodic goods and 25% in the secondary. For the measurement of the qualitative attributes of the shopping areas, respondents were asked to score attributes on a five-point scale from *very poor* to *very good*. Moreover, they had to score the shop areas closest to their home location and thus not necessarily those they spent most of their shopping budget in. This avoids a too positive bias towards those shopping areas that are most frequented. Table 4.1 gives an overview on how the respondents were surveyed on the qualitative assessment of the shopping areas in the respondent's vicinity. The processed results are publicly available [74].

Qualitative shopping attributes to score *On a scale from 1 to 5...*
...How do you score the quality of the stores present in the shopping area?
...How do you score the atmosphere in the shopping area?
...How do you score the presence of gastronomic facilities in the shopping area?
...How do you score the local accessibility of the shopping area by car?
...How do you score the accessibility of the shopping area by public transportation?

Table 4.1: The quantitative assessment of the shopping areas in the respondent's city.

The different shopping areas in Flanders and their format (city center, shopping mall or shopping strip) are derived from Locatus, a provider of an in-field database for stores and shopping areas in Belgium. This database was also used to link stated location choice in the survey. A spatial cluster of stores is classified as a city center when it was located near a historic center and the comprising stores are in walking distance from one another. A shopping mall is identified by the tenants being located in the same building. A shopping strip, finally, is characterized by being located along a major traffic axis to which each comprising store is connected. Because of the specific spatial structuring along a single axis, this format is also characterized by a larger spatial distribution of stores. In total 1,013 coherent shopping areas are found in Flanders. Stores can also be located outside one of these three formats, usually in a spatially diffused way. The survey recorded stated shopping choice to this residual category as well, but we did not take this category into account in this study because no qualitative attributes were surveyed for this category and no reliable spatial metrics can be constructed.

Shopping area performance metric

We estimate the performance for periodic goods sales of each shopping area i as follows (see equation 4.1 for the formula): First, we count within each Flemish municipality the primary and the secondary shopping location choices from the survey for this area. Next, we multiply the two counts by respectively 0.75 and 0.25, which is in line with the survey premises on shopping location choice and budget expenditure. After that, we sum these counts together: the result can now be seen as survey-level full (expenditure) equivalents per municipality. We abbreviate this by 'FEQ's'. To obtain survey-size independent FEQ's per municipality, we divide the FEQ's by the number of respondents per municipality that stated the focal area as either primary or secondary choice, and we multiply this market share-like ratio by the entire population of the municipality. In a last step, we sum the FEQ allocations over all municipalities in Flanders and divide it by the total sales surface of the periodic-goods tenants of the focal shopping area. As a result, we obtain a sales space productivity ratio -FEQ's per m^2- per shopping area i (SP_i) that is known in retail as a key indicator of retail success (sales per square meter or SPSM):

$$SP_i = \frac{\sum_{m \in M} \frac{0.75 \cdot N^p_{mi} + 0.25 \cdot N^s_{mi}}{N^p_{mi} + N^s_{mi}} \cdot P_m}{A_i} \tag{4.1}$$

with N^p_{mi} the number of respondents from municipality m that quoted shopping area i as their primary shopping location for periodic goods. N^p_{mi} is its secondary choice equivalent. P_m is the total population in municipality m. M is the total set of 308 municipalities in Flanders. A_i is the total sales surface of tenants of shopping area i that sell periodic goods.

Scope reduction

We reduce the set of 1,013 shopping areas to those that had at least 30 different qualitative assessments to obtain sufficient sample sizes. Moreover, because of the simplified stated shopping expenditure survey method (maximum of two location choices with an assumed 75% / 25% budget allocation), we expect significant measurement errors for shopping areas that are chosen less frequently (mostly the smaller ones). For larger shopping areas with more choice respondents, we assume the measurement error to be smallest because they exhibit the highest degree of result aggregation and hence overall error reduction. As a result, we limit the number of shopping areas that will be evaluated further to the largest 150 areas in terms of FEQ allocation. The total survey is hence reduced from an original size of 28,000 to the relevant 16,000 surveys. Table 4.2 gives a descriptive overview on the studied set of shopping areas per area format. Figure 4.1 shows the spatial distribution of the selected shopping areas per format on a map. A more detailed zoom-in around the Antwerp area can be seen in 4.2.

Shopping area	nr of shopping	periodic goods sales surface (m^2)			FEQ allocation			Space productivity (FEQ/m^2)				Nr of respondents		
format	areas in scope	Min	Avg	Max	Min	Avg	Max	Min	Avg	StDev	Max	Min	Avg	Max
City centers	96	2 115	13 321	148 205	3 197	37 310	464 828	0.49	2.45	1.05	5.53	60	119	699
Shopping strips	48	2 713	9 486	22 687	3 032	10 735	49 621	0.38	1.20	0.48	2.43	38	92	238
Shopping malls	6	10 060	17 492	30 063	14 394	70 239	171 265	0.89	3.42	2.10	5.85	56	118	255
Total / Averages	150	2 115	11 625	148 205	3 032	30 157	464 828	0.38	2.09	1.16	5.85	38	110	699

Table 4.2: Descriptive overview of the shopping areas and formats in scope.

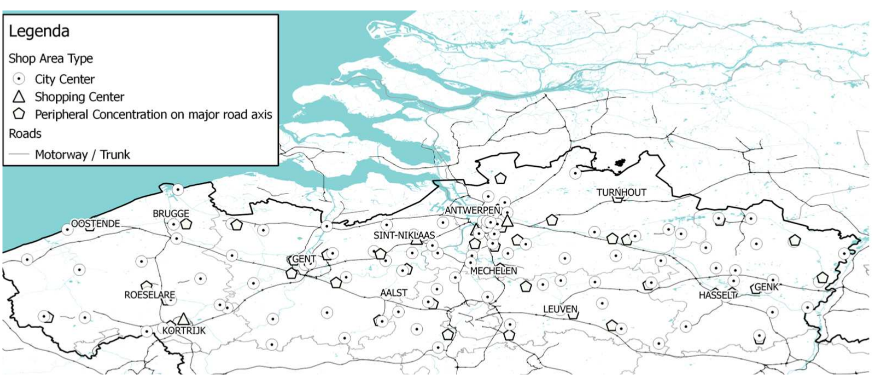

Figure 4.1: Distribution of the studied shopping areas in Flanders, Belgium.

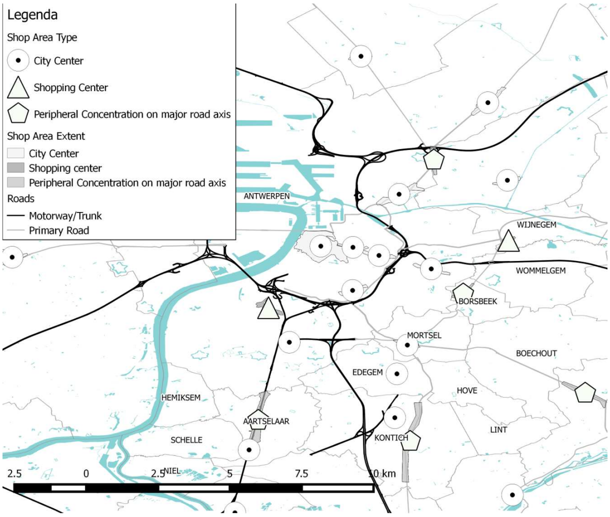

Figure 4.2: Distribution of the studied shopping areas in the Antwerp region, Belgium.

Spatial metrics

In order to explain shopping area success, it is not sufficient to look solely at attributes of the chosen area, but to extend this to the complete shopping area set from which that specific area was chosen by the respondents. In addition, the intertwined role of two prime attributes towards location choice was discussed in section 4.3 (travel cost and agglomeration size) and should jointly be accounted for. As a result, we have chosen to include a metric that jointly captures these attributes within the set of alternative choices for local consumers. As outlined in section 1.2.2, a spatial interaction model is ideally suited to this end as, in its basic formulation, it predicts shopping location probability related to relative distance and size within a choice set. By using spatial interaction modeling techniques, we can calculate a theoretical visit probability within the expected customer attraction zone of a shopping area. A high visit probability indicates that the shopping area is highly preferred within its attraction area due to proximity and agglomeration size. It is constructed in a 3-step approach: First, we determine per shopping area the set of administrative zones (2,644 in Flanders) where the focal shopping area is likely to be part of the choice set of its residents. To this end, we use the respondents' shopping area choices: we allocate each respondent's residential origin to its administrative zone and we calculate a road network based driving time to the primary and secondary shopping location. This gives us an outline of the surveyed trade areas for each shopping area (disregarding whether it is of primary or secondary choice). Subsequently, we use a linear regression technique to obtain a robust estimation of the spatial extent of the choice set presence of each shopping area (i.e. independent of the surveyed shopping choices). We integrate the sales surface (SP_i) as an independent variable because of the known relationship between agglomeration size and spatial customer attraction. The resulting spatial choice set extent D_i^{max} (see formula 4.2) covers on average 90% of the respondents that stated visiting shopping area i. In turn, we identify all administrative zones z where $D_{iz} \leq D_i^{max}$ as the set of zones where shopping area i is in the choice set.

$$D_i^{max} = 30 + 0.0002 \cdot SP_i \tag{4.2}$$

Secondly, we list the full shopping area choice set for each zone z. This per-zone choice set (C_z) corresponds with all shopping areas k that have this zone within their maximum choice set extent D_k^{max}. Per zone z, we then calculate a theoretical, spatial-interaction model-based visit probability of each shopping area in the choice set C_z (equation 4.3):

$$F_{zi} = \frac{SP_i / \exp(D_{zi} \cdot \beta)}{\sum_{k=1}^{C_z} SP_k / \exp(D_{zk} \cdot \beta)} \tag{4.3}$$

with F_{zi} the visit probability of shopping area i for consumers of zone z based on the agglomeration size SP and distance D. β is a distance decay parameter that was fixed to 0.15 based on earlier experience in spatial interaction modeling on shopping area level.

Thirdly, in order to have a representative average visit probability per shopping area i across all zones z within its spatial choice set extent D_i^{max}, equation 4.4 averages the relative visit probability per zone z by weighting it to the population size P_z:

$$WF_i = \frac{\sum_{\forall z | D_{zi} \leqslant D_i^{max}} F_{zi} \cdot P_z}{\sum_{\forall z | D_{zi} \leqslant D_i^{max}} P_z} \tag{4.4}$$

with WF_i ($0 \leq WF_i \leq 1$) as the theoretical, weighted average visit probability for shopping area i. We point out that formula 4.4 disregards the absolute size of local population, while this is a known driver for store success. We remind however, that the construct of sales performance also disregards the absolute size of the shopping area (FEQ per m^2). In abstracting absolute size on demand and supply side, we hence assume a local demand-supply equilibrium throughout Flanders. The resulting probabilities per shopping area are discussed in section 4.5.1.

A second applied spatial metric refers to density economies within a shopping area. As mentioned in section 4.3, a dense, convenient structuring of tenants entices a better perceived shopping experience. We use a spatial point pattern analysis metric (the K-function) that is frequently used in geographic studies on co-location and spatial repulsion [64, 80, 84, 89, 104]. Equation 4.5 gives the mathematical representation of the K-function:

$$K(h) = \frac{R}{n^2} \sum_{i \neq j} \sum I_h(d_{ij}) \tag{4.5}$$

where n is the number of locations in an area R and d_{ij} is the distance between locations i and j. $I_h(d_{ij})$ is an indicator function that equals 1 if $d_{ij} \leq h$.

In this study, we apply this function to the location data of the tenants within each shopping area in scope. Therefore, we fix h to 300 meters as there is general agreement that a maximum distance of 300 meters is an easy walking distance between stores [86, 132]. Equation 4.6 then returns the average percentage of stores that can be found within 300 meters of one another ($0 \leq C(300m) \leq 1$):

$$C(300m) = \frac{\sum_{i \neq j} \sum I_{300m}(d_{ij})}{n^2} \tag{4.6}$$

Figure 4.3 gives an example of a high tenant-density shopping area (high C-index; panel A) and a low tenant-density shopping area (low C-index; panel B). The resulting C-indexes per shopping area are discussed in section 4.5.1.

Figure 4.3: Example of a high C-index shopping area (Panel A) and a low C-index shopping area (Panel B).

4.5 Results and Discussion

In this section, we aim to find relations between the attributes and the space productivity of the shopping areas in scope. First, we present descriptive results on how attributes and space productivity are distributed among the different shopping area formats. Secondly, we perform a multiple linear regression across all formats where the aforementioned attributes are normalized and used as independent variables to explain the normalized metric of shopping area performance. Lastly, we estimate separate regressions per format enabling us to find differences in the way attributes contribute to performance within different formats.

4.5.1 Descriptive statistics

Space productivity

Table 4.2 and joint Figure 4.4 indicate that shopping malls have the highest average space productivity, followed by city centers. Shopping strips exhibit on average the lowest space productivity for periodic goods. On the other hand, lease prices tend to be lower for this peripheral type of shopping area, which could justify the continued viability of shopping-oriented stores in these areas. In the next parts we try to further explain this difference in performance by looking at varying attribute scores among the different formats.

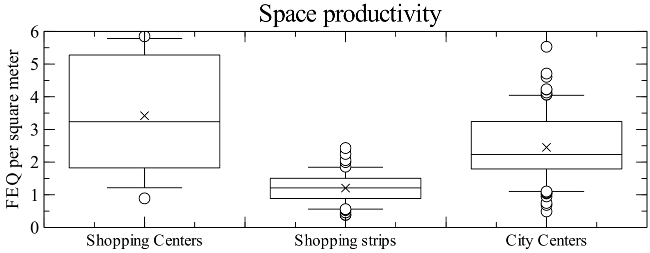

Figure 4.4: Boxplots of the distribution of space productivity for each shopping area format.

Qualitative attributes

Figure 4.5 shows that, on average, shopping malls and city centers are scored equally on accessibility through public transportation (PT), while shopping strips lag behind. A shopping strip is usually located along a major road axis connecting two or more towns, while public transportation facilities are more developed within town agglomerations rather than between two towns. On the other hand, shopping strips have received a high average score on local accessibility by car, far exceeding city centers. City centers are known for heavy local traffic and limited parking with higher parking fees, which is reflected in their score. These scores are in line with findings by Lo and Philippe [91] who also rated peripheral shopping locations as, on average, better accessible by car than city centers. Shopping malls exhibit, on average, the highest score on car accessibility. Similar to shopping strips, they are usually located along major roads with free parking but have, by contrast, a single parking lot shared by all tenants, which contributes to the perceived local accessibility by car. City centers and shopping malls have superior scores for gastronomic facilities. City centers are known for their social role [91] which is reflected in the perceived adequacy of cafes and restaurants. Shopping malls deliberately try to mimic this social aspect in order to attract more customers [8, 56], which is also reflected in their score on gastronomic facilities. The low score for shopping strips clearly indicates that this format generally does not emphasize the social context of shopping. The score on perceived presence of unique stores (quality of tenants) is also tied between shopping malls and city centers, while shopping strips lag behind. Shopping malls invest a lot in the shopping atmosphere and according to the survey results, this is indeed positively reflected in the perceived atmosphere. Again, shopping strips are quoted with the lowest average score.

Spatial metrics

Figure 4.6 shows the theoretical spatial visit probability and C-index statistics per shopping

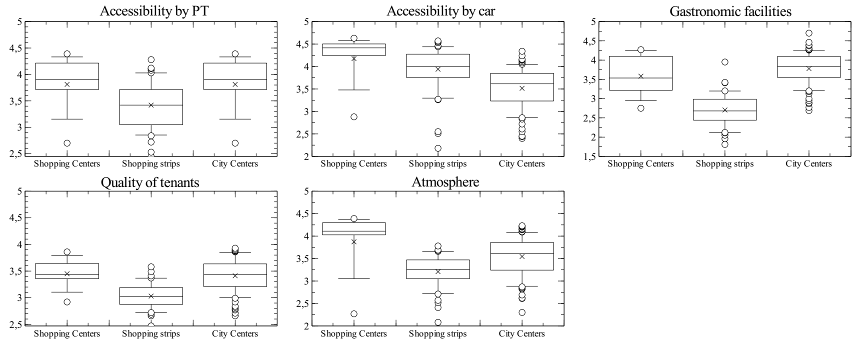

Figure 4.5: Boxplots of the distribution of scored attributes per shopping area format.

area format. As outlined earlier, a low theoretical visit probability indicates that there are larger agglomerations (independent of format) in close proximity of consumers that consider the focal shopping area. A high value indicates that the shopping area has a strong position within its catchment area vis-à-vis alternative shopping destinations. Shopping malls in Flanders tend to have, on average, the highest theoretical visit probability. Aided by their superior macro-accessibility compared to city centers, the travel time towards this format is often lower than towards local city center alternatives. Moreover, they are often among the largest local agglomerations. City centers exhibit a wide range of theoretical visit probabilities, indicating a broad variety in size and macro-accessibility. Shopping malls clearly exhibit superior C-indexes to city centers and shopping strips. This implies that all of the stores comprising the shopping malls are located much closer to one another. Shopping strips on the other hand, are located along a major road axis resulting in the largest inter-store distances.

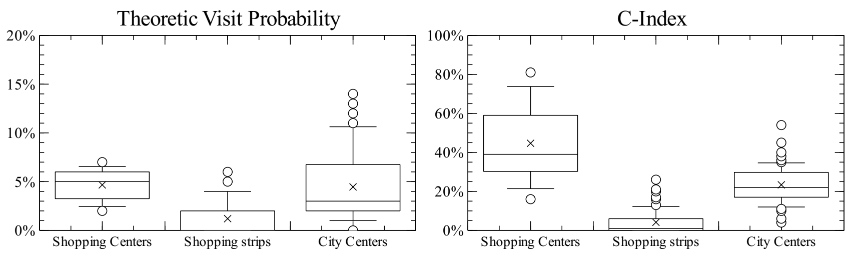

Figure 4.6: Boxplots of the distribution of the spatial metrics per shopping area format.

4.5.2 General linear regression

In this paragraph, we try to identify the general impact of the attributes on shopping area performance across all formats. To avoid the risk of multicollinearity, the tenant and gastronomy facility quality scores were dropped as they correlated significantly with the perceived atmosphere score (73% and 56% respectively). Table 4.3 shows the results of the multiple linear regression across all shopping areas (N=150). 47% of the variation in space productivity could be explained by the model ($R^2 = 0.471$). All attributes are significant at $p < 0.05$ except the perceived accessibility of public transportation.

attribute	coefficient	standard error	T-statistic
Intercept	-1.34	0.94	-1.42
Normalized C-index	1.87	0.61	3.06 **
Normalized theoretical visit probability	9.07	2.58	3.52 **
Normalized perceived atmosphere	1.00	0.19	5.43**
Normalized perceived accessibility by car	-0.44	0.15	-2.94**
Normalized perceived accessibility by public transportation	0.26	0.18	1.41

** significant at 0.05 level — * significant at 0.1 level

Table 4.3: Multiple linear regression results for all shopping areas.

The positive coefficient of the C-index indicates that the more densely clustered the shopping-oriented retailers are within the shopping area, the more it contributes to the average individual success of the tenants comprising it. This confirms findings in previous studies (e.g. Dellaert et al. [37]). The positive coefficient of the theoretical visit probability also seconds results from previous studies on the important positive effects of proximity and agglomeration on shopping area attractivity. The perceived atmosphere is found to be the foremost contributor to shopping area success. Apparently, the positive emotions and feelings the surroundings of a shopping area can elicit, are of primary importance to shoppers in their location choice. A study by Anselmsson [3] indeed confirmed that investments in atmospheric elements yielded an increased numbers of shoppers. An interesting finding is that the qualitative scoring of car accessibility has a negative sign. We explain this mainly by the above-average representation of city centers in the studied set (65%). City centers are characterized by a poorly rated car accessibility but exhibit, on average, high space productivity for shopping-oriented goods (see section 4.4). To discern varying impact within each format however, we present separate estimations per individual shopping area format in the next parts. Finally, the perceived accessibility of a shopping area by public transportation does not appear to have a significant impact on shopping area performance and hence can be seen as more of a political and environmental leverage rather than an economic leverage.

The results enable us to explain why shopping strips exhibit on average the lowest space productivity. Shopping strips score on average lowest on C-index, theoretical visit probability and perceived atmosphere, while these attributes are now shown to contribute positively and significantly to space productivity for periodic goods.

4.5.3 Within-format linear regressions

Figures 4.5 and 4.6 showed that different shopping area formats differ significantly along perceived attributes and spatial metrics. Also, Arnold and Reynolds [8] showed that shopping motivations differ among the shoppers they interviewed. Some were more product and destination driven that valued minimization of travel time and a good accessibility over, for example, aesthetic appeal of a shopping area. Others, seeking gratification or social contact, showed the inverse preference hierarchy. Hence, different shopping motivations can influence the choice of a shopping area format that best suit these motivations, before the actual shopping location choice is made. Because different shopping area formats can attract shoppers with specific motivation patterns, it is reasonable to assume its performance is also driven by shoppers that value attributes differently [91]. In this part, we therefore aim to find varying degrees to which the attributes explain performance within each shopping area format. Because Flanders has only 6 shopping malls within the top 150-ranked shopping areas, we unfortunately limited the within-format regressions to city centers and shopping strips.

For the 96 city centers in scope, a high correlation was found between the perceived atmosphere and the perceived tenant and catering quality (82% and 71% respectively), and between the perceived accessibility by car and the C-index (51%). Hence, to avoid multicollinearity, the perceived tenant and catering quality and the C-index were not used in the regression analysis. Table 4.4 shows the results of the multiple linear regression explaining the sales performance for city centers. It explains 36.6% (adjusted $R^2 = 0.366$) of the variance in space productivity within the set of city centers. All attributes are significant at $p < 0.05$ except, again, the perceived accessibility of public transportation.

attribute	coefficient	standard error	T-statistic
Intercept	0.58	1.23	0.47
Normalized theoretical visit probability	7.32	2.84	2.58 **
Normalized perceived atmosphere	0.99	0.23	4.34 **
Normalized accessibility by car	-0.46	0.22	-2.10 **
Normalized accessibility by public transportation	-0.09	0.24	-0.38

** significant at 0.05 level — * significant at 0.1 level

Table 4.4: Multiple linear regression results for city centers.

Local spatial proximity and agglomeration size that underly the theoretical visit probability are significant drivers for sales performance within the city center format, which is in line with the overall regression. Also, the perceived atmosphere within a city center significantly contributes to its performance. Because atmosphere is highly correlated to the tenant and gastronomy quality in a city center context, it corroborates the social aspect of shopping in city centers [8, 56] as well as the importance of anchor stores [46]. In turn, the sign of the perceived local accessibility by car is persistently negative. This peculiar finding can be related to research by Mingardo and van Meerkerk [94] who found that better performing shopping areas charged on average higher parking fees. According to the authors, these shopping areas could charge more because consumers were willing to pay these higher fees to visit highly attractive shopping areas. This higher attraction stems from the size of retail supply and ample other facilities in a city center. The larger travel and parking cost can be overcome by the superior utility derived from fulfilling multiple activities and purposes in one visit to a city center. Moreover, Arnold and Reynolds [8] and Gilboa and Vilnai-Yavetz [56] found a particular shopping motive that brings another feasible explanation: a less accessible shopping area might benefit from a specific desire to divert from the daily routine (which is usually headed towards well-accessible retail agglomerations that limit travel costs) in the context of pleasure shopping. To the extreme, less reachable shop areas might thereby enhance the shopping 'expedition'feeling. The latter can obviously only take place if the shopping area itself has attributes that yield higher shopping pleasure or superior shopping experiences. Because a lower score on local car accessibility could be inherent to better performing city centers (an increased success lowers the relative supply of parking facilities and could increase parking fees), the results indicate that city centers have other leverages that could compensate for a poor local accessibility by car. Nonetheless, the results should not indicate that local accessibility by car is to be neglected by urban planners. More and cheaper parking could increase the commercial success of city center even more.

For the 48 shopping strips in scope, a high correlation is found between the perceived atmosphere and car accessibility (58%) and, strangely, a high, negative correlation between the perceived accessibility by public transportation and the perceived adequacy of gastronomy facilities (-58%). Therefore, the perceived atmosphere and gastronomy scores are not taken into account in this part. Table 4.5 shows the results of the multiple linear regression. It explains just under 10% (adjusted $R^2 = 0.098$) of variance in sales performance within the set of shopping strips. Only the perceived accessibility by car is significant at $p < 0.1$. The low explanatory power can be justified by the large spectrum of possible tenant configurations within this format. As mentioned earlier, other types of retail offering (e.g. supermarkets; furniture, electronics or DIY stores) are usually geographically mixed with retailers of periodic goods in these strips. Arentze et al. [7] then showed that retailers can benefit from co-locating with retailers selling a different type of goods. This research is however limited to retailers of periodic goods, hence the explanatory power within this format is limited.

attribute	coefficient	standard error	T-statistic
Intercept	-1.14	1.28	-0.89
Normalized C-index	-0.82	1.23	-0.67
Normalized theoretical visit probability	-4.11	5.35	-0.77
Normalized accessibility by car	0.31	0.16	0.06 *
Normalized accessibility by public transportation	0.17	0.19	0.92
Normalized perceived tenat quality	0.23	0.32	0.72

** significant at 0.05 level — * significant at 0.1 level

Table 4.5: Multiple linear regression results for shopping strips.

The perceived accessibility by car is the only significant and positive driver found for improved sales performance within shopping strips. This finding is an indicator that this shopping area format attracts a different type of customers than city centers. More product and destination oriented consumers do not have a specific expectation regarding tenant diversity or quality as they probably have an a priori fixed store visit list. To them, a good accessibility by car is important to minimize time cost. This can also indicate why the perceived atmosphere is positively correlated with car accessibility for shopping strips: a good atmosphere for destination-driven shopping could refer to overlapping elements of good car accessibility: easy parking and store-entry that yield an efficient shopping experience. By contrast, consumers that frequent city centers to combine pure shopping with social or other activities have a more social or other activity based definition of 'a good atmosphere'.

4.6 Conclusions and Limitations

This chapter used the results of a large-scale telephone survey on shopping location choice for periodic goods and the qualitative assessment of various shopping area attributes in Flanders, Belgium. The qualitative metrics were supplemented with two spatial metrics in order to measure their impact on shopping area performance (full expenditure equivalents per m^2). In line with previous studies, it was found that, in general, the intertwined effects of spatial consumer proximity and agglomeration size accrue sales performance, next to a superior shopping atmosphere, and a dense spatial tenant configuration that facilitates easy shopping linkages. However, the perceived micro-accessibility by car and public transportation yielded respectively a contra-intuitive negative relationship and a non-significant relationship. Separate analyses were also made for different shopping area formats (city centers and out-of-town shopping strips) to discover varying attribute importance. When estimating performance within the set of city centers, similar attribute impacts were obtained. In city centers, it was also noted that the perceived atmosphere closely linked to notions of tenant and gastronomy quality, reinforcing the social role of a city center and the impact of having anchor stores on 'shopping experience'. The persistent negative impact of perceived accessibility by car indicated that a badly perceived local accessibility by car could be inherent to high commercial city center success. More successful city centers will struggle to have adequate parking facilities and this could actively increase parking fees. City centers can compensate for this by offering ample opportunities of combining pure shopping with other available activities in a city center (e.g. social or cultural) which offsets the higher costs of travel time and parking fees. Also, if superior shopping experiences are offered in the shopping area, a shopping trip can then be seen as out-of-the-ordinary 'adventure'. By contrast, the perceived accessibility by car was the sole relevant and positive driver for improved sales performance for out-of-town shopping strips. Moreover, the perceived atmosphere of shopping strips correlated significantly with this attribute. The positive correlation between atmosphere and tenant and gastronomy quality for city centers while atmosphere correlates positively with car accessibility for shopping strips, implies that the two shopping area formats attract shoppers with different motives and purposes that jointly value shopping atmosphere in a positive way but define it differently. Shoppers that prefer city centers are looking for experiences or ideas, or see shopping as a social affair [8]. To them, atmosphere is more linked to the available quality of stores and gastronomy facilities. By contrast, shoppers that prefer shopping strips to buy periodic goods are more likely to perceive easy and cheap parking and store access as a good shopping atmosphere.

This distinction is important as the perceived atmosphere contributes to sales performance within all formats and is regarded as one of the most manageable leverages for urban planners or shopping site managers [130]. By surveying what elements exactly constitute the perceived shopping atmosphere of shopping areas that scored highest *within* the focal format, urban planners and shopping site managers can define the right actions towards increasing success. Especially in regard to increased pressure of e-retail on physical shopping area performance, Singleton et al. [121] showed that investments in leisure and social facilities are seen as an important tool for the resilience of physical shopping areas. In this study, we showed that city centers (and hence urban planners) have a superior leverage to this end. By contrast, shopping strips have less leverages towards retaining their profile of shoppers, because of easy access to online retailing platforms and home-delivery.

The findings of this research are also important towards a more accurate prediction of single-store performance. The spatial interaction model, that is also used for the theoretical visit probability metric in this study, is often applied to this end. In this type of model, the utility derived from store attributes is estimated. We can now extend the utility function with the scores of significant attributes of its superordinate shopping area. As a result, the inclusion of the car-accessibility attribute should yield a varying impact on the turnover prediction of a store that is either located in a city center or located along a shopping strip. Although the use of a Flemish questionnaire limits the applicability of the qualitative attributes to the Flanders area, we advance that the spatial metric for density economies within the shopping area (the C-index) can be added to the store-utility function across geographic markets in a straightforward way.

At this chapter's conclusion, we acknowledge that this study exhibits significant limitations. First, it relies on the results of a survey that enquired about shopping location in a simplified and approximate way. The survey only registered the two most important locations per respondent and applied an approximate assumption on budget representation (75% & 25%). This introduces a significant amount of measurement error and hence, we are forced to limit the shopping areas under study to the largest ones to limit this error and obtain feasible space productivity values. The conclusions are thus drawn from a subset of the entire shopping area population in Flanders. As a result, we cannot guarantee the generalization of results towards all sizes found in the shopping area population. Secondly, the measurement error is probably enhanced due to surveying stated shopping location behaviour, instead of observed choice behaviour. The latter is indeed preferred for the construction of performance metrics, but is harder to collect on shopping area level. Thirdly, we are bounded in this study to the spatial configuration, size and historic context of cities and inhabitants in Flanders. This resulted in an imbalance of the different shopping area formats in the limited set. City centers are for example historically among the largest and most common retail centers in Flanders. The limited city size and policy restrictions can in turn explain the limited number of large shopping malls in Flanders. Therefore, no separate analysis could be made for shopping malls in this study. Fourthly, the assumed local equilibrium between demand and supply in Flanders is likely not to correspond to reality. Some areas will suffer from a higher degree of supply saturation than others, resulting in a lower average space productivity. Ideally, an attribute that reflects local demand-supply imbalance is incorporated when predicting shopping area performance. Fifthly, as pointed out throughout this chapter, several other influencing attributes can be added to the regression model: (a) buying-situation based factors as consumer characteristics (e.g. income), tasks and purposes in regard to shopping; (b) the presence of retail offering of other types of goods, especially in regard to shopping strip performance; (c) other tenant-related factors that were not surveyed or measured in this study: promotions and price/value perception, available entertainment or friendliness of personnel. Finally, follow-up research should corroborate the conclusion that the definition of perceived atmosphere differs across different types of shoppers and shopping areas.

5
Conclusion

5.1 Results Summary

Previous chapters illustrated in detail the various contributions made to a better understanding of spatial consumer behaviour in retailing. This improved understanding resulted from looking at observed consumer behaviour (a) from various angles, (b) for different retailers and (c) with different analytical procedures. First, we used different angles to analyze consumer behaviour that range from the consumer's relative location towards multiple same-branded stores in chapter 3 to the spatial configuration and observed success of a shopping area in chapter 4. Secondly, we simultaneously examined customer origin information for multiple retailers in chapter 3, and in chapter 4, we studied commercial success across all co-locating retailers on the aggregate shopping area level. Thirdly, the applied analytical procedures ranged from more descriptive plots of consumer behaviour in chapter 3 to a fully specified spatial interaction model in chapter 2. Nonetheless, we are of the opinion that the findings of each chapter can be summarized jointly by looking at them as different tools in an extended modeling toolbox. This extended toolbox allows the reader to construct a spatial interaction model with higher accuracy than before.

In the remainder of this section, we demonstrate relative improvements in predictive power upon integrating and testing different novel building blocks in a SIM. While these individual percentages might seem small at times, we argue that their joint impact should be considered and, as we will discuss in section 5.2, even a slight improvement in predictive performance of a SIM can have a major impact on investment decision making for a retailer.

Store attributes

A first category of extended tools in the SIM toolbox encompasses store (agglomeration) related attributes. For starters, chapter 2 described the impact of the brand of a retailer on individual store success. This impact was split into a global brand attractiveness factor and a local brand representation factor. First, the global attractiveness parameter was constructed by calculating the average sales space productivity across all stores of each retailer in scope. This was motivated by the observation that more attractive brands exhibit an increased average sales space productivity (see section 1.2.2.2). By incorporating this fixed value per retailer in the attractiveness component of a store and applying it to the Belgian grocery market, the Mean Absolute Percentage Error (MAPE) on retailer level was reduced with nearly 20 percentage points. Secondly, the local brand representation factor was calculated per consumer origin area as the share of stores of the focal brand in the set of all competitor and own stores within a radius around a consumer origin area. By incorporating this factor as a positive attraction attribute in the interaction component of the same SIM, a slight improvement in MAPE on store level was found (0.67 percentage points).

Moreover, chapter 2 showed that the explicit modeling of multiple store concepts yields significant improvements to the predictive power of a SIM. Each grocery store on the Belgian food market was allocated to a store concept based on its sales area size (local grocery store, supermarket or hypermarket). In turn, each store concept was attributed its own basic attraction component and distance decay parameter to be optimized. This resulted on the one hand in hypermarkets having wider trade areas with only moderate decrease in local market share with increasing distance and on the other hand, in local grocery stores having very narrow trade areas with high local market share decay when distance increases. By applying it to the Belgian food market, spectacular improvements in MAPE of more than 8 percentage points on store performance level were found.

In chapter 3, the impact of neighbouring retail on a store's spatial competitiveness for customers was examined. Depending on the type of products offered by a retailer and the retailer's location strategy, different degrees of positive impact of neighbouring retail were found. For a retailer of periodic (shopping) goods that focuses on high street locations, the positive agglomeration effects were largest, with up to 20 percentage points more sales attraction towards a store in a large retail agglomeration, originating from an area of spatial competition with another of the retailer's stores located in a small retail agglomeration. For the supermarket retailer however, positive agglomeration effects were barely detected. An interesting finding was that for another studied retailer of periodic goods, no significant positive agglomeration effects were found either, showing that intra-network competition also depends on the brand strength of a retailer and that an individual analysis per retailer is needed when incorporating these dynamics in a SIM.

Chapter 4 dived deeper into the underlying drivers of retail agglomeration success. With the results of a telephone survey on shopping area choice in Flanders, a space productivity metric was calculated reflecting shopping area performance for periodic goods. Superior spatial consumer proximity and agglomeration size improved sales performance of city centers and shopping malls over peripheral shopping strips, as well as a better perceived shopping atmosphere and a dense spatial tenant configuration. For city centers, the perceived atmosphere closely linked to tenant and gastronomy quality, while for shopping strips a good atmosphere linked to a good local accessibility by car. The latter is also the sole positive driver found for shopping strip performance. This led to the conclusion that the perceived shopping atmosphere is important to the performance of each shopping area format, but its definition is different across formats as it depends on the different shopping motivations of the type of customers each format attracts.

Consumer demand

A second category of extended tools applies to an improved estimation of consumer demand. Chapter 2 extended current spatial interaction modeling by incorporating a factor for demand substitution (or elasticity). When local store supply is low for goods from the retail segment under study, consumers will more actively seek for substitutes for these products. This leads to a fraction of the actual demand not being allocated to modeled supply. By contrast, in case there is ample local supply, it could trigger above-par demand as convenience and choice is high. This is an important integration in SIM as it allows for the estimation of local market creation when simulating a store opening. By contrast, when closing a store, the reduction in local demand can also be estimated, which reduces the recovery potential for nearby stores. This dynamic is of course depending on the retail segment under study, and a separate analysis of this demand elasticity is thus required.

Interaction between demand and supply

A third category of extended tools involves the impact of distance between consumer and store. Chapter 2 used two different metrics for calculating distance between consumers and stores: a euclidean, straight-line distance and a travel time that was based on actual vehicle routing over the road network. The use of the routed travel times yielded significantly better predictive performance over the use of euclidean distances: over 3.5 percentage points reduction on store-level MAPE. However, an even better performance over routed travel times came from using the average of both the euclidean and routed travel time: around 0.8 percentage points improvement on store level MAPE over the sole use of routed travel times. This outcome showed that physical proximity, independent of the local road configuration, has a moderate reinforcing effect on store choice in the Belgian food market.

Next, chapters 2 and 3 elaborated on the concept of sales cannibalization within a retailer's store network. Sales (or internal) cannibalization refers to the spatial store choice dynamics of consumers that have different stores of the same retailer nearby. As offering in these stores is usually very similar, internal competition within a network tends to be fierce. For example, the impact on the sales of an existing store, generated by a new store opening nearby, is expected to be significant, especially in an area where the new store yields higher utility (due to for example closer proximity). Chapter 2 incorporated this dynamic in a SIM by firstly calculating unrelated attraction values per consumer origin area for all nearby stores of one retailer. These values reflected independent store preference. Subsequently, a penalty to their respective attraction values was then calculated that increased with the ranking of attractivity of each store. Applied to the Belgian grocery market, this yielded an improvement on store-level MAPE of more than 1 percentage point. In chapter 3, this spatial choice dynamic was mapped from a relative distance point-of-view for multiple retailers across different retail segments. It was shown that for grocery retailing a marginally closer location to a consumer shifted the store visiting preference heavily towards that store. This resulted in clearly separated store trade areas based on distance. For more fashion-oriented (periodic goods) retailers, we found less intra-network competition based on relative distance, hence trade areas of different stores often overlapped. These observed differences in spatial competition shape expansion strategies: while the grocery retailer clearly has to opt for blind spots in his network as expansion cases, other retailers can even have multiple outlets close to one another (e.g. in the same shopping area) without detrimental mutual sales cannibalization.

Finally, in chapter 2, an extension on the interaction component of a SIM was proposed that incorporated attraction penalties for sociocultural borders that have to be traversed between the consumer and the store. For example, in the case of the Belgian market, different linguistic areas exist. The incorporation of penalties thus limited the attraction of stores for consumers beyond a sociocultural border.

Model optimization

A final category of tools relates to the optimization of a spatial interaction model. Chapter 2 proposes a particular meta-heuristic to optimize the model parameters. The Multi-Objective Simulated Annealing (MOSA) algorithm uses observed consumer behaviour on three different levels: customer origin area-level based on loyalty card data of one retailer (i.e. spatial expenditure flows towards each store), store-level turnovers for the same retailer and enterprise-level turnovers for competitors. This contrasts with the current common practice in SIM optimization that focuses solely on single-level validation. By optimizing the parameters with joint validation on these three levels, more robust store location predictions can be made. This robustness stems for example from the fact that competitor stores are now -on average- reflecting the right attraction on the market. This ensures, to a certain degree, the spatial stability of predictions across an entire country as the basic attraction of local competitor stores (before taking specific store, interaction and demand features into account) is as closely fit to the observed average attraction by these competitors on a national level. On the other hand, by looking at deviations on the expenditure flow level during model optimization, the right spatially driven dynamics (like sales cannibalization) are incorporated and fine-tuned.

5.2 SIM Applicability and Added Value

Throughout the retailing process, several stakeholders can be identified that can benefit from the high explanatory and predictive capabilities of the SIM and its extensions proposed in this dissertation. The presented extensions on SIM have been applied to the markets of many retailers (and other stakeholders) in Belgium and the Netherlands. The following added values reflect our observed benefits for these stakeholders. And, while such model can appear as very complex and expensive in setup, this hesitation threshold can be lowered significantly when such a model is embedded in a Spatial Decision-Support System (SDSS) aimed at showing the added values within a few clicks and hiding the complexity when preferred by the end-user.

For retailers

First of all, several use cases for an extended SIM can be found for retailers faced with location-based decisions. Various types of these decisions have been summarized by Hernandez et al. [63] as *6 R's*, each with their respective decision horizon and involved investment risk (Figure 5.1).

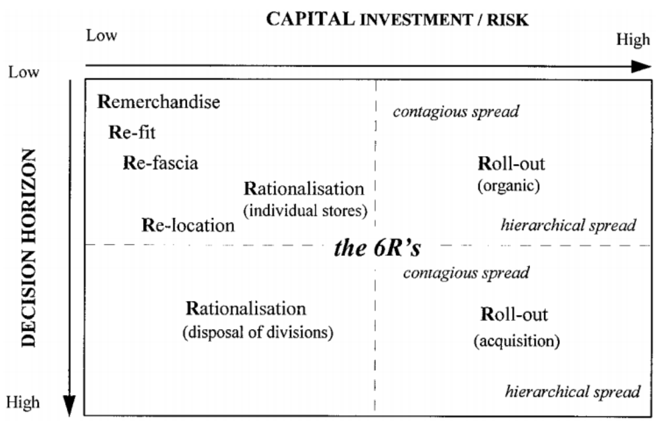

Figure 5.1: Location-based decision types for retailers with decision horizon and capital investment. Reprinted from Hernandez et al. [63].

The most straightforward use case is to forecast the performance of a store location (*Roll-out* in Figure 5.1). Reynolds and Wood [112] state that in the UK, location planners see themselves mainly in support of the financial business case for store expansions. An accurate estimation is indeed nowadays vital to convince boards of directors or shareholders to invest in a new store location. Wood and Tasker [140] argue that in the UK market a 10% deviation in a sales forecast for a medium-sized grocery store could change the bid for a site by more than 5 million Euros [1]. Even when a vacant store property is leased, an accurate estimation of the store's potential is vital as lease commitments can span multiple decades with very high severance pays [63]. In these cases, a retailer is especially wary for an overestimation of the performance by the model, as it leads to an unprofitable store. On the other hand, if predictions are made more conservative to this end, it increases the opportunity cost for this location as a competitor might seize this location for its own expansion. Usually, the trade-off is made in favour of a slightly more conservative prediction.

A special use case on location forecasting can be put up as a result of the contributions made in this dissertation. When a new store opens in a region where the retailer's network is already dense, there is a significant risk that it will partially cannibalize the turnover of neighbouring stores of this retailer [70]. With the explicit integration of intra-network sales cannibalization dynamics in a SIM, the impact on the performance of neighbouring stores can be quantified more accurately. As a result, the net impact on the entire network can be used as a second site evaluation criterion next to the forecasted annual turnover for the new store (see Figure 5.2). Imagine an expansion case in which the expected turnover of a location under study is estimated as high as well as the expected impact on neighbouring stores in terms of sales cannibalization. Because such result is detrimental for the existing stores, it can indicate to reconsider the expansion case in favour of enlarging the existing neighbouring stores over opening that new store. This could mitigate the risk of sales cannibalization while the increased attractiveness of the enlarged stores enables them to capture the existing upwards potential. For retailers running multiple store concepts, the case could even be rerun with a smaller or more complementary store concept in the retailer's portfolio that is known to have far less cannibalization interaction with the concepts of the surrounding stores.

A second use case can be made for retailers that are not looking for expansion, but rather for re-optimizations and rationalizations (closings) in their store network (*Rationalisation* and *Re-location* in Figure 5.1). A SIM can readily withdraw a store from the set of destinations after which the expenditure flows are recalculated to the remaining destinations. This recalculation then gives the location planner insights in what turnover is being recovered by the remaining network or channels and what amount is lost to competition or substitution. In this regard, the integration of sales cannibalization and demand elasticity in a SIM is of great added value to estimate the sales recovery potential with a high degree of accuracy. In case of a store remodeling, the attractiveness component of that store is adapted and the expenditure flows are recalculated. A similar business case evaluation with both store and network related forecasts can then be made.

A third, overarching use case can be found in the use of a SIM to design network plans on a strategic level. This design involves the opening and closing of multiple stores at once, which the SIM can easily facilitate. Also, assumptions on consumer behaviour evolutions on a longer term can be integrated by adapting the parameters or input of the SIM. Moreover, novel supply channels (like *e-commerce*) can be integrated in the SIM [126]. To this end, a

[1] Wood and Tasker [140] quote £5 million in their original paper.

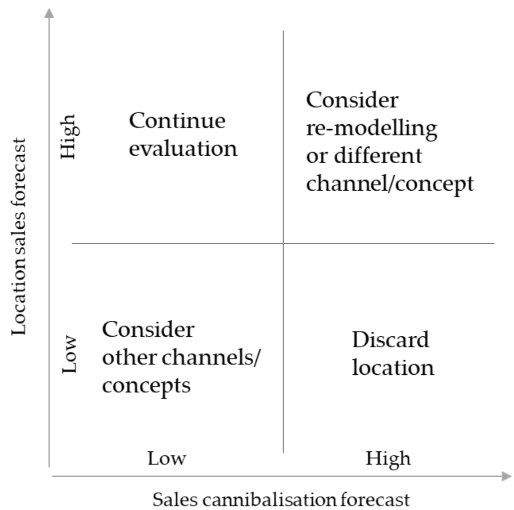

Figure 5.2: Site evaluation based on predicted store turnover and predicted sales cannibalization.

suggestion for future research on their incorporation in a SIM is proposed in section 5.3.2.

A fourth and final use case can be made on a more operational level. A SIM can be used to monitor active store performance against forecasts (benchmarking). When looking for causes of deviations between both, a deep-dive analysis on observed and forecasted local market share from all customer origins in the catchment area can yield insights in some spatial causes and possible counter-actions. For example, when certain areas do not yield market shares as expected by the model, targeted communication campaigns or a more aggressive price setting could be tested.

While a spatial interaction model has a multitude of use cases for retailers, the setup of such a SIM requires a significant setup track (and cost). As shown in section 5.1, various SIM building blocks have to be analyzed from the focal retailer's specific point-of-view. As a result, a SIM is not available 'off the shelve' and a tailored data-gathering, model formulation, optimization and testing trajectory has to be set up. The length and complexity of such a trajectory depends on the segment of retail. Some segments of retail show less complex consumer behaviour, resulting in a less complex model formulation (with less tools from the SIM toolbox required for good model performance), while other segments are characterized by complex, intertwined consumer behaviour requiring a full model specification (see Birkin et al. [16] as well). Figure 5.3 shows the evolution of model complexity across retail segments that was discovered through the application of a SIM for different types of retailers.

Complexity of spatial interaction model formulation

Moderate → **High**

Product segment	Daily goods	Specialty goods	Periodic (Shopping) goods	Service oriented retail
Examples	Grocery markets	DIY, electronics & furniture	Clothing, shoes	Filling stations / Catering/ service offices
Major attraction drivers	Convenience (distance), size, brand	Distance, size, neigbouring retail (mainly specialty & daily)	Retail agglomeration (size & quality), atmospherics & gastronomic facilities	Proximity to and between various activity locations: footfall
Major modeling efforts	Sales cannibalization	Sales cannibalization, trade area extent as function of size and agglomeration	Consumer behavior towards shopping areas rather than individual stores	Impact of 'occasional' footfall vs classic distance-constrained interactions (destination visits)

Figure 5.3: Spatial interaction modeling complexity for different retail segments.

For retail real estate developers

Retail real estate developers conceptualize, build and manage facilities of retail development projects. These projects range from individual stores to larger multi-store retail centers. A first use case for SIM that brings added value for them, is a direct outcome from the analyses of chapter 4. During this research different drivers of shopping area success were found, with some drivers manageable on shorter term during exploitation (atmospherics, tenant and gastronomy quality) while others are more structural that should be considered during the early conceptualization phase (location & store concentration). These drivers of success can be seen as leverages for these developers to avoid vacancies [38] and to drive retail floor space leasing prices [50].

Another use case in this context consists of building a SIM in which the supply side is up-scaled from individual stores to the more aggregate shopping area level. The market demand, in turn, is updated to a spending potential on a broader product class (f.e. '*fashion*'). Such an up-scaled model where shopping areas compete with one another for a broader expenditure potential, can then be used to forecast the high-level success of their planned development in the retailing market. These forecasts can be used as a tool to convince retailers to lease sales area in the new development. Also, such a SIM can be used to actively search for high-potential development locations. For example, a prototype of a retail development can be modeled with an iterative procedure in each town, yielding a shortlist of towns with high-performance forecasts that can be examined further for specific opportunities.

For government officials

A final stakeholder in the retailing process is the government. In a retail context, government officials grant development permissions, and urban planners develop broader retail policies and are responsible for the public domain around stores or retail developments (like roads). They can be interested in using an up-scaled SIM as described in the previous paragraph, as it can forecast the continued liveability in terms of mobility and neighbouring retail when a new retail development applies for permission:

Concerning mobility, a SIM can model the expected trade area of a planned retail development including expenditure flows from each consumer origin. With reasonable assumptions, these fluxes can be transformed into annual car visitor numbers from each origin. Subsequently, the most likely travel routes per origin towards the development can be calculated (using shortest-path algorithms for example). When the different per-origin travel routes are merged and crossed with expected annual visitors per car and current traffic congestion information, the impact of a new retail development on existing, structural traffic jams can be estimated.

Concerning neighbouring retail, government officials often aim at assuring continued viability of retail in city centers that are under pressure from peripheral developments. As mentioned in the paragraph for retailer added value, a SIM is able to forecast performance impact on neighbouring retailers. With the aid of an up-scaled model for retail center attraction, such objective estimation of the expected impact on city center retail performance can be made. Its outcome can be used re-actively for the evaluation and permission granting of the planned peripheral development [108] or pro-actively for retail development policy making (defining no-retail-development zones around city centers for example).

5.3 Suggestions for Future Research

The previous chapters provided valuable building blocks for the improvement of the accuracy of a SIM in a retail context. At the conclusion of this dissertation, it is in no way assumed that such a model is now final. Continuous improvements can be made to the model as additional and more relevant datasets and better model optimization methods appear and deep-dive knowledge on customer behaviour is gained through the use and evaluation in a SIM.

A number of suggestions for continued research have surfaced throughout the conducted research. They can be grouped into three major categories: (a) integration of new data sources in a SIM, (b) extensions on the SIM formulation and (c) improvements on optimizing SIM's.

5.3.1 Integration of new data-sources in SIM

Several new sources of high-quality data that can be useful to improve modeling and understanding spatial consumer behaviour, have emerged or find themselves at the brink of emerging.

A first such source consists of very time-detailed information on actual traveling speeds over the entire road network of a country. The actual speed profiles are usually collected through GPS data of many thousands of cars. These historical data can be provided as fine as per time frame of 10 minutes. Local traffic jam profiles within a store's catchment area can be calculated for these time frames and these profiles could be matched with synchronous time series on the store's performance. This could lead to a more accurate estimation of the varying impact of congested traffic on store turnover. Moreover, for longer term SIM forecasting, structural speed profiles can be calculated as averages of observed speeds within the opening hours of a store. The question was then raised by Birkin et al. [16] if peak visit hours should be weighted more in such profile and to what degree. An assessment on the weighting structure that provides the best predictive capabilities for a SIM could significantly improve the forecasting performance of a SIM for all retail in highly traffic-congested areas.

Another promising data source that draws more attention from both academics and practitioners is the full-scale captation of mobile data. Mobile data are the registration of the geo-localization of a consumer through apps with tracking capabilities (GPS) [72, 95] or through triangulation based on captured signal strengths on radio pylons of the consumer's telco provider [9, 67]. Based on different localizations around the time of a store's visit, the entire physical customer journey can be mapped for a great share of a store's customers.

First, by mapping these journeys, much more and richer observed consumers flows can be gathered for optimizing the SIM. For example, the telephone survey that was used in chapter 4, could be scaled to a much larger population than the 16 000 consumers used in that research, providing much more rich and nuanced data (for example, it would yield data on actual behaviour instead of stated behaviour from the survey).

Secondly, it would provide a significant breakthrough in the construction of store trade areas without the need of loyalty card information. Even actual trade areas of competitor stores could be mapped.

Thirdly, it would give first-time insight into local trip chaining behaviour around a store on a very large population scale. This could lead to improved demand disaggregation where customers are allocated to multiple origins based on the locations of their recurrent stays around a store rather than using solely and separately their residential or workplace origin as practiced in current SIM's.

Fourthly, a more accurate interaction component between the local consumers and a store can be calculated. The classic approach in a SIM calculates travel distances or travel-times between the location of the consumer origin on one side and the location of a store on the other side. With the use of mobile data to capture physical consumer journeys between recurrent stays, the travel-time to a store can now be based on the actual detour travel time from existing trips between local recurrent stays and a probability component can be added that a store visit would be included between two recurrent stays, based on observed trip chaining between the context of each stay and a store visit.

However, great care has to be given to potential privacy issues. It is known from literature that using mobile data for hypertargeting can result in a boomerang effect [48].

5.3.2 Extensions on the SIM formulation

Next to using richer data-sources, the SIM formulation can also be extended or improved. The suggestions made next envelop a better model formulation on the impact of store (environment) features, the adaptation of the SIM formulation for service oriented retailers as well as the incorporation of new channels of supply that have emerged.

In the presented research the mapping of the store environment is limited to retail activities. The amount and quality of neighbouring retail is taken into account in the SIM as a positive driver for store attraction, as combining visits to multiple stores in one stop provides a higher utility to consumers. As pointed out in section 1.2.2.2, the scope of activities can be extended beyond retail, either through demand disaggregation or residential trip-chaining. In regard to residential trip-chaining, Arentze et al. [6] developed an agent-based, multi-activity, multi-stop location choice model in which they discovered a negative relation to chaining stops and activities with rising distance but a positive relationship with the size of each activity. A more pragmatic approach can be taken to incorporating these findings in the store utility function of a SIM to bolster predictive capabilities. Many alternative activities (next to residential and retail) can be mapped for the geographic scope of the SIM: workplaces, schools, healthcare and leisure or cultural venues (see section 1.3.4). Next, these locations can be enriched with information on the size of the activity taking place through the use of specific web-crawling techniques or by cross-matching the locations with Open Data sources. For example, data on the number of hospital beds or the number of students in a school can greatly improve the weight that has to be given to trip-chaining between these activities and a neighbouring store. Moreover, a weight can be attributed to each type of activity, catching the likeliness of chaining a visit to the activity and the neighbouring store (depending on the trip purpose) in one trip. For example, visits to a hospital and a furniture store are less likely to be chained in one trip, while a gift shop and a hospital are perfect candidates for trip chaining. Finally, the specific distance between the store and the location of the activity can be taken into account with the importance of a neighbouring activity in trip-chaining diminishing as the distance between both increases. Figure 5.4 gives a graphical example of various neighbouring activities of different types, sizes and distance to a focal store.

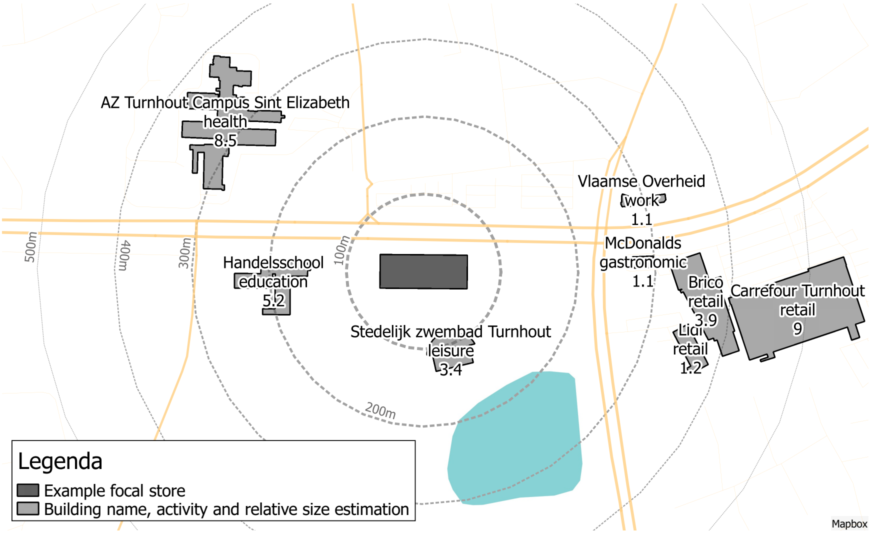

Figure 5.4: Example of neighbouring activities around a focal store.

By accounting for the aforementioned elements, a total chaining weight per specific activity location can be modeled, catching the size and purpose-driven chaining-likelihood of the activity in relation to each store. The total weight of all activities in the store's environment can then be calculated as a measure of the store's *activity centrality*, and can be integrated as a store attractiveness feature in spatial interaction model formulation. The presence of such activities around a store can then be seen as a driver for residential attraction towards that store. Similar methodological approaches have been used in literature to estimate local agglomeration effects: Piovani et al. [105], for example, used an exponential distance decay of nearby Foursquare check-ins to forecast site valuations and found a maximum interaction range of 325m.

Current research was conducted on retailers offering different categories of products. However, a SIM can equally be constructed for service retailers like banks. In these markets however, slightly different rules apply as consumers are usually affiliated with a particular service provider through a contract. Since a SIM models expenditure flows representing a consumer *action*, we suggest that a SIM for service providers should rather forecast the *delta's* in local affiliation in relation to its office network: churn and acquisition. While the other instruments of the service marketing mix play a big role (e.g. service offering and communication), looking to churn and acquisition from a spatial point of view could yield interesting complementary insights. For example, the impact of relative proximity of competing service provider offices on local churn and acquisition can drive strategic office network decisions.

In the contemporary retailing context, an important improvement encompasses the integration of other, non-physical sales channels in a SIM [17, 126]. *Virtual* retail channels like e-commerce that deliver the ordered goods at home have no true physical location for the consumer, hence no real customer flow or distance based on a physical separation can be calculated in a SIM. Nonetheless, spatial interactions with consumers and even physical stores can exist, depending on the type of offered products by the retailer and the way the goods are delivered:

- For low-tech products like books it can be assumed that a negative spatial interaction exists between physical stores and the virtual channel. The virtual channel will be more successful in areas located at larger distances from a physical store: as the travel cost to a physical store increases, the relative utility of the virtual channel increases simultaneously for consumers. Nonetheless, a physical store might see its revenue cannibalized even at closer distances.

- For high-tech products, a positive spatial interaction between the virtual channel and the physical store could be noted. This means that a virtual channel has more success at closer distances to a physical store than in more remote areas. As these products have a higher risk of malfunctioning, consumers exhibit the desire to make physical contact with the vendor of the product explaining their problem and seeing a solution proposed. The possible travel cost associated with such visit can already be taken into account during the initial purchase process.

- In a third case, when the virtual channel ships orders to be picked-up at a specific (third party) location (like a supermarket), the pick-up points can be seen as 'stores' exerting a positive attraction on consumers nearby due to low travel cost. It can be expected that such attraction is more spatially constrained than towards a physical store.

- Finally, the sociodemographic profile of each consumer origin in scope can be used to incorporate a varying inclination to shop online. Many market reports exist on the online shopping frequencies of population subgroups. However, given the rapidly growing popularity of e-shopping across all sections of the population, forward-looking inclinations to e-shopping of these subgroups are paramount to support long-term physical network decisions.

One basic way -that merits further development- to integrate a virtual channel in a SIM is by treating this channel as a *virtual* store which has a fixed, small, *virtual* travel time between itself and all consumer origins. The virtual store has no specific attraction features but the size of the attributed virtual travel time can be varied to match its true performance in the market. From a technical modeling point of view, this is very similar to the demand elasticity factor presented in chapter 2. However, this factor then still needs to be fine-tuned in its observed spatial interaction with physical stores.

5.3.3 Improvements on SIM optimization

Machine Learning (ML) algorithms have been put forward in section 1.2.1 as showing great promise for improved captation of complex consumer behaviour as they do not assume an a priori model formulation. Instead, during the ML procedure, the model formulation itself is discovered and optimized based on pattern recognition in the data. This often leads to an increased model performance but also to an increased model complexity, where due to the latter, the model can appear as a black box. This makes the validation of an ML model by human understanding and common sense a much more difficult task. Moreover, only a limited number of observations is usually available to which an ML model is optimized. Observed expenditure flows are mapped on aggregated consumer origin zones rather than individual customer level. This resulted for example in chapter 2 in 27,143 observations for the supermarket chain. Given that limited number of observations, risk of overfitting the data is a real threat, especially when the ML algorithm ultimately aims at a continuous rather than a broad turnover class prediction and is getting gradually more complex in its model formulation and parameter optimization through multiple iterations. The lack of straightforward understanding of the final model and the risk of overfitting due to a limited number of observations endanger the robustness of a predictive ML-driven model, while its innate performance (in terms of goodness-of-fit) could be very good. For retail location planners, robustness of a model usually prevails over possible superior performance. Their focus is on limiting outliers and having an understandable model to communicate and elaborate the performance forecasts internally. To that end, they usually prefer the use of a fixed model formulation (a SIM for example) and optimize such model with statistical estimators or (meta-)heuristics.

A suggestion for future research is proposed that seeks the middle ground between both approaches, capitalizing on their mutual strengths. A 2-step automated procedure can be constructed where in the first phase a SIM is used after which in the second phase an ML algorithm is applied to model the deviations of the first phase. In a first phase, a SIM is optimized using well-known techniques like statistical estimation. This results in well-understandable, robust forecasts, even with a limited number of observations. In the second phase, an ML algorithm aims at improving overall goodness-of-fit as it attempts to find a-priori unknown patterns in consumer behaviour by forecasting the deviations of the observations of the SIM step. Applying an ML algorithm in a second step can have several benefits:

- The first step already explained a substantial part of the observed consumer behaviour. As a result, only a limited depth of the ML model is needed in the second step, guaranteeing an easier understanding of the patterns of consumer behaviour found by the ML algorithm and limiting the risk of overfitting.
- The ML model formulation can capture very non-linear concepts of consumer behaviour, thereby improving the goodness-of-fit of the first step. This improvement on goodness of fit in the second step might be limited at first sight but such increase

in accuracy of forecasts can be very significant for a retailer and its competitive edge as shown in section 5.2.

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